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# Idiosyncratic Information and the Cost of Equity Capital: A Meta-Analytic Review of the Literature

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This paper provides a quantitative review of the literature on the repercussions of idiosyncratic information on firms' cost of equity (CoE) capital. In total, I reconsider the results of 113 unique studies examining the CoE effects of information *Quantity*, *Precision* and *Asymmetry*. My results suggest that the association between firm-specific information and CoE is subject to moderate effects. First, the link between *Quantity* and CoE is moderated by disclosure types and country-level factors in that firms in comparatively weakly regulated countries tend to enjoy up to four times greater CoE benefits from more expansive disclosure—depending on the type of disclosure—than firms in strongly regulated markets. Second, a negative relationship between *Precision* and CoE is only significant in studies using non-accrual quality proxies for *Precision* and risk factor-based (RFB)/valuation model-based (VMB) proxies for CoE. Third, almost all VMB studies confirm the positive association between *Asymmetry* and CoE, but there is notable variation in the conclusions reached when *ex post* CoE measurers are used.

*Keywords:* meta-analysis; idiosyncratic information; information risk; expected returns; cost of equity capital; implied cost of capital

# Idiosyncratic Information and the Cost of Equity Capital: A Meta-Analytic Review of the Literature

## 1 Introduction

Extensive literature in accounting and finance investigates the extent to which idiosyncratic information affects price formation and return structures in capital markets. This strand of research commonly tests the proposition that firms with high (low) quality information environments should enjoy relatively low (high) cost of equity (CoE) capital. Specifically, it is conjectured that firms can lower their CoE if they disclose more value-relevant information to investors (*Quantity*), provide information of higher accuracy (*Precision*) and disseminate information more widely between investor groups (*Asymmetry*). While analytical works have modelled these propositions elegantly (e.g., Diamond and Verrecchia (1991), Easley and O'Hara (2004), and Lambert, Leuz and Verrecchia (2012)), the empirical evidence regarding their predictions is mixed (e.g., Core, Guay, and Verdi (2008), McInnis (2010), and Mohanram and Rajgopal (2009)).

Given, on the one hand, that the proper measurement of a firm's CoE (*alias* expected rate of returns) is an ongoing debate in itself (e.g., Botosan and Plumlee (2005), and Easton and Monahan (2016)), and, on the other hand, that proxies for the information attributes (i.e., *Quantity*, *Precision*, *Asymmetry*) are large in number, as informed by both accounting and finance research, the empirical literature is voluminous and the conclusions reached vary widely depending on the proxies used by researchers. With that in mind, the main objective of this paper is to offer a systematic review of the extant literature to examine the reasons underlying the variation in results. In particular, this review meta-analyses the associations of *Quantity* and *Precision* with CoE and provides a descriptive summary of extant findings on the link between *Asymmetry* and CoE.[1,2] To the best of my knowledge, this is the first study to quantitatively summarize

[1] Meta-analysis is a statistical approach that summarizes empirical findings of multiple studies. Meta-analysis techniques require the use of effect size which—in meta-analytic accounting research—is commonly the study's Pearson $r$ correlation coefficient between the dependent and independent variable of interest (Hunter, Schmidt, and Jackson (1982), Khlif and Chalmers (2015)).

[2] Given vast variation in research designs between studies examining the impact of *Asymmetry* on CoE (e.g., some studies use yearly, others monthly data; some focus on portfolio-level, other on firm-level) a meta-analysis is not feasible; hence, I focus on descriptive statistics only when examining this link.

all the links between idiosyncratic information and CoE within a unified framework. As such, it complements narrative literature reviews on this topic (e.g., Artiach and Clarkson (2011), Beyer, Cohen, Lys, and Walther (2010), Healy and Palepu (2001), and Kothari, So, and Verdi (2016)) and extends Souissi and Khlif (2012) who focus on disclosure (*Quantity*) effects only.[3]

# 2 Theoretical Background and Research Hypotheses

To facilitate the structure of this review, I present a conceptual framework based on which I select the studies in my sample (see Figure 1). The direct links between *Quantity*, *Precision*, *Asymmetry* and CoE are widely consistent with analytical work (e.g., Easley and O'Hara (2004), Clarkson, Guedes, and Thompson (1996), and Lewellen and Shanken (2002)) and substantiated by empirical evidence. Next, I provide a succinct narrative review of some notable studies examining the CoE effects of firm-specific information in order to pinpoint prevailing debates in the extant work, reveal commonly used information proxies, and offer guidance towards the creation of meaningful subgroups in later analyses.

(Figure 1 about here)

## 2.1 Information Quantity and Cost of Equity

Literature on estimation risk demonstrates that if the amount of information about a firm is low, investors have difficulties to accurately estimate the return and cash flow parameters of this particular firm. This parameter uncertainty makes such firms a riskier investment vis-à-vis otherwise comparable firms, and hence induces higher CoE (e.g., Clarkson et al. (1996), and Lewellen and Shanken (2002)). A significant proportion of the literature examines the association between *Quantity* and firms' CoE, with 56 such papers analyzed in this study. One stream of research uses simple proxies—such as firm age or period of listing—as measures of information quantity and shows that these prox-

[3] Similar to this study, Souissi and Khlif (2012) also meta-analyze the link between disclosure and CoE; however, my analysis differs from theirs in that it operates a larger sample (56 vs. 22 studies), covers a longer sampling period (1997-2010 vs. 1997-2017) and analyses substantially more firm-years (342,116 vs 9,553). Furthermore, I include both mandatory and voluntary disclosure studies, while Souissi and Khlif (2012) focus on voluntary disclosure only.

ies are negatively correlated with CoE (e.g., Barry and Brown (1984, 1985), Clarkson and Thompson (1990), Kumar, Sorescu, Boehme, and Danielsen (2008), and Zhang (2006)). A second stream uses firms' disclosure levels as proxies for *Quantity* and ample evidence exists confirming a negative association with CoE (e.g., Baginski and Rakow (2012), Botosan (1997), Campbell, Chen, Dhaliwal, Lu, and Steele (2014), Cao, Myers, Tsang, and Yang (2017), Healy, Hutton, and Palepu (1999), Francis, Khurana, and Pereira (2005), Fu, Kraft, and Zhang (2012), Kothari, Li, and Short (2009), and Ng and Rezaee (2015)). Thus, I formulate Hypothesis 1:

**H1:** The larger (smaller) the quantity of available information about a firm, the lower (higher) its CoE.

## 2.2 Information Precision and Cost of Equity

In a seminal paper, Easley and O'Hara (2004) demonstrate that a firm's CoE decreases with the accuracy of available information about the future value of the firm. Essentially, this means that investors demand to be rewarded for bearing uncertainty about a firm's prospects stemming from imprecise information given to them, implying that firms that disclose higher quality information to investors can benefit from reduced CoE. This proposition is thoroughly researched in the literature (e.g., 38 papers are assigned to this link in my analysis) and the extant work can be categorized into two major strands: *accounting/earnings quality* and *security analyst forecast*-based studies.

The first stream is pioneered by Francis, La Fond, Olsson and Shipper (2004, 2005). The authors examine the association between the quality of accounting information and CoE, and demonstrate that firms' CoE decreases as their earnings quality measures increase (e.g., accrual quality, value relevance). However, in an influential paper, Core, Guay and Verdi (2008) strongly question the validity of these early results. Despite continuous evidence for the proposition that earnings/accounting quality is negatively related to CoE (e.g., Aboody, Hughes, and Liu (2005), Barth, Konchitchki, and Landsman (2013), and Hou (2015)), this link is challenged in a number of papers (e.g., Cohen (2008), Khan (2008), and McInnis (2010)).

The second stream of research uses security analyst forecasts to proxy for information precision. Extant literature argues that the less uncertainty exists about the prospects of a firm, the greater the consensus among security analysts and the more precise their forecasts (e.g., Barry and Brown (1985), Barron and Stuerke (1998), and Barron, Kim, Lim, and Stevens (1998)). Botosan and Plumlee (2013) provide evidence that total analyst forecast precision (AFP) is negatively associated with CoE. Botosan et al. (2004) decompose total analyst forecast precision into private and public information components and show that public (private) AFP is negatively (positively) associated with CoE. Interestingly, Barron, Sheng, and Thevenot (2012) find that for firms with limited public information, private AFP is in fact *negatively* associated with CoE. This might be explained by the dual effect of private information precision. On the one hand, more precise private information might increase information asymmetry, which then induces higher CoE (e.g., Diamond and Verrecchia (1991)) but, on the other hand, it might also decrease CoE when the quantity of public information is limited. Simply put, private information is still better than no information at all (Easley and O'Hara (2004), Lambert et al. (2012)). Given this empirical evidence along with the analytical insights from Easley and O'Hara (2004), I formulate Hypothesis 2:

**H2:** The higher (lower) the information precision of a firm, the lower (higher) its CoE.

## 2.3 Information Asymmetry and Cost of Equity

Easley and O'Hara (2004) furthermore show that as the fraction of uninformed investors as well as the number of private signals about the future value of the firm increases, its CoE also increases: uninformed investors—who only have access to public information—require compensation for "losing out" to privately informed investors—who have access to both public and private information—when making investment decisions. The greater these informational disadvantages are, the larger the CoE premium induced by *Asymmetry*. Numerous papers investigate this conjecture empirically (e.g., 22 such papers are included in my analysis) and mainly use market microstructure proxies (e.g., PIN scores, bid-ask spreads) to gauge the degree of informational disparity between investor groups.[4,5] Easley, Hvidkjaer and O'Hara (2002) were the first to doc-

[4] PIN scores measure the probability that the next trade order is from a privately informed investor; i.e., based on private information, with higher PIN scores signifying greater *Asymmetry*. The notion underlying the PIN model is that while it is impossible to directly observe which trades are based on private

ument a positive association between CoE and PIN scores. Conversely, Mohanram and Rajgopal (2009, p. 241) conclude that "there is not much evidence to support the interpretation that information risk, proxied by PIN, is a source of priced information risk." However, these authors acknowledge that while their paper suggests "PIN is not priced risk, it is difficult to make more general statements about the pricing of information risk since information risk can […] be proxied by different empirical variables". In fact, using spread-based proxies, Amihud and Mendelson (1986), Bhattacharya, Ecker, Olsson, and Schipper (2012), and Levi and Zhang (2015)—among others—document a significantly positive association with CoE. This corroborates Hypothesis 3:

**H3:** The higher (lower) the information asymmetry between investors, the higher (lower) the firm's CoE.

## 2.4 Summary of Prior Empirical Evidence

The extant empirical evidence may be summarized as follows. First, whenever the link between *Quantity* and CoE is tested, the current research prefers using disclosure instead of simple proxies for information quantity as indicated by 56 studies using the former and only five studies using the latter (i.e., Barry and Brown (1984, 1985), Clarkson and Thompson (1990), Kumar et al. (2008), and Zhang (2006)). However, it should be noted that proxies for disclosure levels tend to measure disclosure along both a quantity and quality dimension, which makes them noisy estimates of *Quantity*.[6] Furthermore, wide variation in research designs, disclosure types examined and disclosure metrics used by researchers all possibly moderate the overall negative relation between disclosure and CoE.[7] Hence, more evidence along the lines of Richardson and Welker

information, one can use imbalances between buy and sell orders to infer the probability of information-based trading for a given stock (e.g., Brown, Hillegeist, and Lo (2004), Easley, Kiefer, O'Hara, and Paperman (1996), and Easley, Kiefer, and O'Hara (1997)).

[5] Bid-ask spreads are a measure of the adverse selection problem market makers are exposed to and assumed to increase with information asymmetry (Copeland and Galai (1983), Glosten and Milgrom (1985)). Jack Treynor, publishing under his pseudonym Walter Bagehot (1971), gives an intuitive explanation as to why greater bid-ask spreads are associated with greater information asymmetry.

[6] For instance, Cheng, Collins, and Huang (2006, p. 179) state that "while prior empirical research has used the *quantity* of disclosure as a proxy for the *quality* of disclosure quality, in many cases disclosure quantity and quality are not separable information attributes."

[7] For instance, some studies investigate mandatory disclosure (e.g., Campbell et al. (2014), and Core, Hail, and Verdi (2015)), while others concentrate on voluntary disclosure aspects (e.g., Botosan and

(2001) and Mangena, Li, and Tauringana (2016) on the types of disclosure that are particularly CoE-relevant seems beneficial. Second, accounting quality, and more specifically earnings quality, appears to be an important determinant of firms' information *Precision*. However, since the study of Core et al. (2008), its association with CoE is subject to controversy. Moreover, CoE tends to decrease with total AFP, but results are mixed for its relationship with the private and public components of analysts' information sets. Third, *Asymmetry* is commonly measured by market microstructure-based proxies, and while there is an ongoing debate about the pricing of PIN (e.g., Botosan and Plumlee (2013), and Duarte and Young (2009)), the negative relationship between bid-ask spreads and firms' CoE seems to be widely accepted.

# 3 Cost of Equity Measurement

Firms' CoE capital is the key variable of interest in this paper and its empirical measurement differs across studies. Some researchers use *ex post* returns to proxy for CoE (e.g., Doukas, Kim, and Pantzalis (2006), and Konchitchki, Luo, Ma, and Wu (2016)), while others apply *ex ante* estimates (e.g., Barth et al. (2013), Bhattacharya et al. (2012), Cohen (2008), and Hou (2015)). I classify those studies that conduct asset pricing tests (i.e., regressing realized returns on possible risk factors) or use average realized returns as CoE proxies as *ex post* and refer to them as realized return-based (REAL) in my analyses. I further divide the remaining "non-REAL" papers, which use *ex ante* CoE specifications, into two categories: risk-factor based (RFB) studies, which calculate CoE by multiplying estimated factor loadings from traditional asset pricing models (e.g., CAPM, FF3) with respective factor returns, and valuation-model based (VMB) studies, which reverse-engineer valuation models (such as the dividend discount, resid-

Plumlee (2002), and Francis, Nanda, and Olsson (2008)); some papers focus on financial disclosure (e.g., Baginski and Rakow (2012), and Evans (2016)), while others examine non-financial disclosure (e.g., Dhaliwal, Li, Tsang, and Yang (2011), and Ng and Rezaee (2012)); and, some authors use self-constructed disclosure scores (e.g., Botosan (1997), and Kothari et al. (2009)), while others rely on commercially available ones (e.g., Healy et al. (1999), and Richardson and Welker (2001)), and yet others use simple dummy variables to distinguish between disclosing and non-disclosing firms (e.g., Ogneva, Subramanyam, and Raghunandan (2007), and Cao et al. (2017)).

ual income or abnormal earnings growth model) to estimate firms' implied cost of capital (ICC).[8,9]

Empirical proxies are, by definition, inherently flawed (Rao, 1973) and so are the aforementioned return measures. For instance, Elton (1999) states: "The use of average realized returns as a proxy for expected returns relies on a belief that information surprises tend to cancel out over the period of a study and realized returns are therefore an unbiased estimate of expected returns. However, I believe that there is ample evidence that this belief is misplaced" (p. 1199). In a similar vein, Fama and French (1997) argue that RFB proxies are "woefully imprecise estimates of the cost of equity" (p. 154) given that these estimates are based on noisy past realized returns. Ultimately, the unexpected news component in realized returns tends to corrupt the reliability of factor loading and factor premia estimates in RFB models. Finally, Easton and Monahan (2005) examine a number of different VMB estimates and conclude that—due to the optimism in analysts' earnings forecasts— "these proxies are unreliable" (p.501). In addition, VMB measures encounter issues arising from firm-specific estimation (e.g., Easton (2009), Wang (2015)) and growth assumptions made by researchers (e.g., Easton (2006)).

Despite these concerns, two major conclusions regarding the empirical validity of the different measures seem justified. First, proxying for CoE by realized returns is problematic in that discount rate and cash-flow news constitute significant impacts on firm-level returns, making realized returns noisy estimates of CoE (e.g., Chen, Da, and Zhao (2013), Ogneva (2012), and Vuolteenaho (2002)). Second, VMB proxies show somewhat greater construct validity than RFB proxies in terms of association with future realized returns, common risk-factors, and predictive power of returns (Botosan and Plumlee (2005), Botosan, Plumlee, and Wen (2011), Lee, So, and Wang (2010, 2015)). Taken together, this suggests that the measurement of CoE might partially explain

8 For a step-wise description of how to operationalize RFB estimates see, for instance, Barth et al. (2013), Landsman, Miller, Peasnell, and Yeh (2011), and O'Hanlon and Steele (2000).

9 The intuition behind the ICC framework is straightforward: use a specific valuation model, accept the current stock price as at least semi-strong efficient and determine the internal rate of return that equates current stock price of the firm with expected future payoffs to shareholders, where future payoffs are commonly proxied by analysts' earnings forecasts. The internal rate of return is then considered the market participants' *ex ante* assessment of the firm's CoE. See Botosan and Plumlee (2002), Claus and Thomas (2001), Easton (2004), Gebhardt, Lee, and Swaminathan (2001), Gode and Mohanram (2003), Gordon and Gordon (1997), and Ohlson and Juettner-Nauroth (2005) for common ICC measures.

mixed results across studies when analyzing the effects of *Quantity*, *Precision* and *Asymmetry* on firms' CoE.

# 4 Methodology

The main objective of this paper is to provide a meta-analytic review of the literature on idiosyncratic information and firms' CoE capital. However, only for H1 and H2 research designs between studies are homogenous enough to carry out meta-analyses. Studies relating to H3 often lack necessary information and data comparability to conduct a meaningful meta-analysis (e.g., sample size information is inconsistently reported; some studies use yearly data, others use monthly data; some focus on the portfolio-level, others focus on the firm-level). Hence, for H3 I only provide descriptive statistics (e.g., fraction of studies confirming/rejecting the hypothesis; proxies used and proportions thereof).

## 4.1 Data Collection and Sample

In line with research hypotheses H1-H3, I search for different combinations of several keywords (shown in Table 1) in the following databases to identify relevant studies: ISI Web of Science; ScienceDirect; Emerald Management Ejournals; and SSRN. A review of all top-tier journals in accounting and finance as well as the reference list of all identified articles complements my search.[10] I exclude analytical papers (e.g., Bertomeu, Beyer, and Dye (2011), Cheynel (2013), Christensen, de la Rosa, and Feltham (2010), Dutta and Nezlobin (2017), Hughes, Liu, and Liu (2007), Lambert, Leuz, and Verrecchia (2007), and Strobl (2013)) and studies lacking statistical information required for the meta-analysis of H1 and H2 (e.g., Aboody et al. (2005), Beneish, Billings, and Hodder (2008), Chen, Shevlin, and Tong (2007), Clement, Frankel, and Miller (2003), and Hirshleifer, Hou, and Teoh (2012)) during this process.

[10] *Accounting Journals:* Accounting Review, Accounting, Organizations and Society, Journal of Accounting and Economics, Journal of Accounting Research, Contemporary Accounting Research, and Review of Accounting Studies; *Finance Journals:* Journal of Finance, Journal of Financial Economics, Review of Financial Studies, Journal of Corporate Finance, Journal of Financial and Quantitative Analysis, Journal of Financial Intermediation, Journal of Money, Credit and Banking, and Review of Finance.

(Table 1 about here)

As noted above, the literature applies various measures for *Quantity*, *Precision*, *Asymmetry* and CoE. Based on the most commonly used proxies in the literature, I create several sub-groups for each information attribute and CoE (see Figure 1) and code each study in my sample accordingly. For instance, Francis et al. (2004) examine the impact of seven different earnings quality measures on two implied cost of capital proxies; hence, I classify this study as using “Accounting Quality” proxies for information precision and “VMB” proxies for CoE. The coding of studies requires my judgment as to which category a paper fits best; hence, this may induce sampling bias in that one might arrive at different classifications for some studies.[11] Moreover, I exclude some insightful papers from the sample because the novelty of the proxies applied in these studies hinders their allocation to one of my sub-groups. For example, El Ghoul, Guedhami, Ni, Pittman, and Saadi (2013) put forward firms’ geographic distance from financial centers as a measure of information asymmetry and show that CoE decreases with proximity; Cao, Myers, Myers, and Omer (2015) find that company reputation is negatively related to CoE, and Muino and Trombetta (2009) document a significant impact of distorted graph disclosure on CoE. Furthermore, I focus on firm-level results, so country-level studies are excluded from the analysis (e.g., Bhattacharya, Daouk, and Welker (2003), and Li (2015)).

## 4.2 Meta-Analysis Techniques

### 4.2.1 Effect Size

Meta-analysis techniques require the use of effect size which—in meta-analytic accounting research—is commonly the study’s Pearson *r* correlation coefficient between the dependent and independent variable of interest (Hunter, Schmidt, and Jackson

[11] For example, Baginski and Rakow (2012) examine the CoE effects of management earnings forecast disclosure policy. They measure disclosure policy as the product of three dimensions: Supplier, Frequency and Precision. Given that (1) their proxy is based on two *Quantity* dimensions (Supplier, Frequency) but only one *Precision* dimension and (2) their main contribution relates to voluntary disclosure—“we extend the literature by examining a specific type of voluntary disclosure rather than disclosure in the aggregate” (p. 317)—I classify their paper as a *Quantity* rather than a *Precision* study.

(1982), Khlif and Chalmers (2015)).[12] If a study only reports regression results, I convert *t*-statistics into *r* coefficients as $\sqrt{t^2/(t^2+df)}$, where *df* is degrees of freedom. If only *p*-values are provided, corresponding $Z$ scores can be obtained from the standard normal table which I then transfer into *r* coefficients by using $Z/\sqrt{N}$, where *N* is sample size (Rosenthal, 1991).

Whenever a study uses multiple, but similar, measures for a variable (say, different proxies for earnings quality), I record the study's average effect size. Therefore, these studies only appear once in the analysis (Ahmed & Courtis, 1999). However, if a study tests different proxies for different samples (say, one RFB and one VMB CoE sample), I record the effect size for each sub-sample separately. Therefore, these studies appear twice in the analysis. To clarify, 56 studies for the link between *Quantity* and CoE contribute 62 observations to my analysis (*Precision*: 35 studies and 48 observations*; Asymmetry*: 22 studies and 28 observations).

Also, where necessary, I multiply a study's effect size by negative one to ensure consistent interpretation across proxies and to conform to the intuition of the underlying hypotheses of this paper. This is required because the interpretation of results varies depending on which proxies are used: some proxies are constructed such that *higher* values also signal higher information quality, while for others *lower* values indicate higher information quality. For instance, in most studies, higher analyst-based measures signal higher *Precision*—confirming H2 if a negative correlation with CoE is observed. In contrast, lower earnings quality proxies usually indicate higher information precision—confirming H2 if a positive, not negative, correlation with CoE is observed. In such instances, I multiply the effect size (of earnings quality) by negative one to reverse and re-align the interpretation of results with the intuition of the underlying hypothesis (H2).

After the effect size for each study is calculated, I estimate the mean correlation ($\bar{r}$) for the population as shown in Eq. (1), where $N_i$ is the sample size and $r_i$ is the Pearson correlation coefficient for study *i*.

$$\bar{r} = \frac{\sum(r_i N_i)}{\sum N_i} \tag{1}$$

[12] I use Spearman correlations, if Pearson correlations are not reported.

The population variance ($S_p^2$) is estimated as the difference between observed variance ($S_r^2$) and the sampling error variance ($S_e^2$) as shown in equations (2) to (4), where $K$ is the total number of studies included in the analysis.

$$S_p^2 = S_r^2 - S_e^2 \tag{2}$$

$$S_r^2 = \frac{\sum N_i (r_i - \bar{r})^2}{\sum N_i} \tag{3}$$

$$S_e^2 = \frac{(1 - \bar{r}^2)^2 K}{\sum N_i} \tag{4}$$

Eventually, I calculate the 95% confidence interval as follows:

$$\left[\bar{r} - S_p Z_{0.975}; \bar{r} + S_p Z_{0.975}\right] = \left[\bar{r} - S_p(1.96); \bar{r} + S_p(1.96)\right] \tag{5}$$

**4.2.2 Homogeneity Tests**

To test for homogeneity in the data—that is, to examine if variation in results is due to sampling errors or moderating effects—two methods are followed. First, I put the sampling error variance into perspective to observed variance ($S_e^2/S_r^2$) to reveal the degree to which the residual variance is trivial: if more than 75 percent of the variation in results can be attributed to sampling error (the suggested cut-off in the literature), then the relation under investigation is considered to be homogenous and unmoderated (Ahmed and Courtis (1999), Khlif and Chalmers (2015), Pearlman, Schmidt, and Hunter (1980)). Second, I calculate the chi-square test statistic shown in equation (6), where high statistical significance rejects the null of homogeneity, indicating that moderating effects might impact upon results across studies (*K-1* is the degrees of freedom and N = $\sum N_i$). While statistically powerful, it should be noted that chi-square statistics are directly proportional to sample size (Fan, Thompson, & Wang, 1999), which makes it difficult to accept homogeneity at conventional levels in large sample studies like this one.

$$\chi^2_{K-1} = \frac{NS_r^2}{(1 - \bar{r}^2)^2} \tag{6}$$

### 4.2.3 Sample Size

Most of the papers analyzed in this study report results for a multi-period sample which poses the question of how to define sample size (i.e., $N_i$) in equations (1) to (6). Using the number of unique firms appears to be most appealing. However, this information is often missing. Conversely, the number of firm-years (firm-quarters or firm-months) is reported most consistently but might bias meta-analytic results towards studies spanning longer sampling periods without necessarily covering more firms. I address this point as follows: when transforming t-statistics (p-values) from regression results into *r* coefficients, I determine the degrees of freedom (sample size) based on the number of observations in the regression (e.g., firm-years). When summarizing among studies (e.g., computing mean effect size, population variance, chi-square statistic), I use the average number of firms (i.e., firm-years divided by number of years) as sample size. This maintains the internal integrity of each study—larger sample studies generate robuster results—while ensuring a "sampling-period-independent" impact on the meta-level.

## 5 Results

Fifty-six (56) studies in my sample examine the link between *Quantity* and CoE, 35 examine the link with *Precision* and 22 examine the link with *Asymmetry*. Given that some papers provide findings for multiple sub-categories (for instance, RFB and VMB proxies), subsequent analyses are based on 62 observations for *Quantity*, 48 observations for *Precision* and 28 for *Asymmetry*. Hereafter, I use "observations" and "studies/papers" interchangeably but results always refer to the number of observations. The *Quantity*, *Precision* and *Asymmetry* studies included in my sample are shown in Table 2, Table 3, and Table 4, respectively. Table 5 summarizes this information and reports descriptive statistics across the entire sample.

(Table 2 about here)

(Table 3 about here)

(Table 4 about here)

(Table 5 about here)

## 5.1 Information Quantity and Cost of Equity

Subsequent meta-analysis is limited to the disclosure literature, given that "simple-proxy" studies are sparse (i.e., Barry and Brown (1984, 1985), Clarkson and Thompson (1990), Kumar et al. (2008), and Zhang (2006)). Sixty-two (62) observations in my sample analyze the link between *Quantity* and CoE of which most pertain to published work (n=50; 81%) and appear in higher-tier journals (37; 60%).[13] Ten percent of studies use realized returns to proxy for CoE (n=6), with VMB measures prevailing in the disclosure literature (VMB: 50; 81%; RFB: 6; 10%). Whilst some studies include firms from multiple countries in their sample (13; 21%), the great majority are single-country studies (49; 79%). Interestingly, only 25 observations (40%) relate to US firms—which is exceptionally low compared to the US-bias in *Precision* and *Asymmetry* studies (81 and 86 percent, respectively)—and the remaining 37 studies either focus on non-US countries (29; 47%) or include inseparably both US and non-US firms (8; 13%) in their samples (see Table 5).

In addition, Table 5 reports the type of disclosure examined and the disclosure metric used by researchers. I categorize 11 observations (18%) as having a clear focus on financial disclosure, 22 (35%) as evaluating non-financial disclosure aspects, and the remaining 29 (47%) as partial-financial (i.e. all studies with an emphasis on the general quality of firms' disclosure). Most studies apply self-constructed indices to measure disclosure levels (38; 61%), followed by thirteen studies (21%) relying on third-party providers (e.g., AIMR, S&P scores) and eleven (18%) observations using simple dummy variables to distinguish between disclosing and non-disclosing firms.

Examining the general conclusion of each paper, about 70 percent of all observations (n=44; 71%) tend to confirm the negative association between *Quantity* and CoE, six studies reject it (10%), and the remaining 12 papers (19%) provide

[13] I refer to journals that have a score of three or four in the ABS 2015 list as higher-tier outlets and denote journals with a score of two and one as well as unraked and unpublished work as lower-tier.

mixed/conditional results for this link. For instance, Francis et al. (2008) show that the negative relation between disclosure and CoE vanishes after controlling for earnings quality; Evans (2016) and Kim and Shi (2011) suggest that the timeliness and the sign of earnings announcements (good/bad) as well as the degree of market competition are important conditioning variables; and Espinosa and Trombetta (2007) and Gietzmann and Ireland (2005) demonstrate that the impact of disclosure on CoE is extenuated by accounting conservatism (i.e., only firms adopting aggressive accounting policies can reduce their CoE by increased disclosure activity). This qualitative assessment is consistent with meta-analytic results (see Table 6). The mean effect size between *Quantity* and CoE is -0.066 with a 95% confidence interval between -0.190 and 0.058, indicating that findings vary across studies. A highly significant $\chi^2$ of 241.21 with 61 degrees of freedom along with only 26 percent of observed variance explained by sampling error ($S_e^2/S_r^2$) rejects the null of homogenous data and pinpoints the presence of moderating effects.

(Table 6 about here)

#### 5.1.1 Measurement of Cost of Equity

Dividing studies according to CoE measurement yields some interesting insights (Table 6, Row II & III). The first sub-group includes those studies which use *ex post* returns (REAL) as proxies for CoE; the second group (RFB/VMB) contains studies applying either risk factor-based or valuation model-based CoE estimates. Total average effect size for the RFB/VMB group ($\bar{r}$: -0.075 ± 0.129) is about three times larger than for the REAL group (-0.026 ± 0.037).[14] However, none of the REAL studies examine the association in a pure financial disclosure setting—where CoE effects are most pronounced—which tends to clarify the difference in effect size (Columns II-IV).[15] More importantly, both effect sizes are insignificantly different from zero (p-value: 0.256 and 0.171), indicating that CoE measurement does *not* explain mixed results in the literature.

[14] Average effect size plus/minus two standard deviations (i.e., $\sqrt{Sp^2}$) of the mean (i.e., 95% interval).

[15] The effect size for VMB proxies ($\bar{r}$: -0.084 ± 0.128) is markedly stronger than for RFB measures ($\bar{r}$: -0.017 ± 0.071) which—as in the case of the REAL group—is attributable to the fact that none of the RFB studies focus on financial disclosure.

### 5.1.2 Measurement of Quantity

Table 6 distinguishes studies according to the type of disclosure examined by researchers: financial (FF), partial-financial (PF) and non-financial (NF) disclosure studies. Row IV shows a statistically significant correlation of about 12 percent between CoE and FF studies (p-value: 0.019), but a markedly reduced and statistically insignificant effect size of only five percent for PF and NF studies (p-values: 0.358 and 0.361). This shows that financial disclosure is twice as important to investors than non-financial and partial-financial disclosure. However, this is not to say that non-financial information is irrelevant. For example, a relatively large strand of research within the NF category (n=10; 16%) documents a significantly negative association between corporate social responsibility (CSR) disclosure and CoE ($\bar{r}$: -0.056 ± 0.022, untabulated).[16] Moreover, findings are robust to researchers' choice of how to measure disclosure levels; irrespective of using self-constructed disclosure indices (SCI) or simple dummy variables to proxy for disclosing and non-disclosing firms, the effect size is always significantly negative for FF studies (SCI: -0.101 ± 0.069; Dummy: -0.126± 0.106), but insignificant and much weaker for NF and PF studies (see Table 7).[17]

(Table 7 about here)

Next, I examine if different disclosure requirements across countries moderate results. In doing so, I categorize my sample in three different ways. First, I distinguish between US and non-US studies. Second, I assign each study a disclosure regulation score and allocate studies with a score below the sample average of 0.83 to the LOW group and the remainder to the HIGH group.[18] Third, I follow Souissi and Khlif (2012) and form groups based on countries' transparency culture, where the high disclosure

[16] CSR studies: Bachoo, Tan, and Wilson (2013), Clarkson, Fang, Li, and Richardson (2013), Déjean and Martinez (2009), Dhaliwal et al. (2011), Dhaliwal, Li, Tsang, and Yang (2014), Ng and Rezaee (2015), Plumlee, Brown, Hayes, and Marshall (2015), Reverte (2012), Richardson and Welker (2001), and Wu, Lin, and Wu (2014).

[17] Given that error variances (*Se²*) for FF and NF studies using externally provided disclosures scores (EXI) are larger than observed variances (*Sr²*), confidence intervals cannot be calculated and a comparison with PF studies is not meaningful.

[18] Consistent with Core et al. (2015), I measure the level of disclosure regulation by the index of disclosure requirements in securities offerings from La Porta, Lopez-De-Silanes, and Shleifer (2006). In the case of multi-country studies, I report a weighted average per observation (weight: firm-years per country).

environment group (HDE) includes studies conducted in the US, UK and Canada, and the low disclosure environment group (LDE) covers the remaining countries.[19]

Table 8, Column V, shows that total disclosure effects are about 3.5 times larger in non-US studies ($\bar{r}$: -0.139) than in US studies (-0.039). Similarly, studies concentrating on less regulated (LOW: -0.126) and less transparent countries (LDE: -0.141) document an approximately 3 times stronger correlation between disclosure and CoE than studies focusing on more regulated and more transparent countries (HIGH: -0.062; HDE: -0.043). However, the magnitude of these differences varies according to disclosure types: the CoE effect of financial disclosure in non-US settings is "only" 2.5 times larger than in US settings, while partial- and non-financial disclosure effects are about 3 and 4.5 times larger (similar patterns can be observed for HIGH and LOW as well as HDE and LDE studies).[20]

Higher mandatory disclosure requirements in the US (and in HIGH/HDE countries) may explain these differences in disclosure effects. Mandatory disclosure replaces and pre-empts benefits from voluntary disclosure, which is least pronounced for financial disclosure where financial reporting quality converges towards a uniform standard across countries (e.g. IFRS/US-GAAP convergence), and most pronounced for non-financial disclosure where the difference in requirements between highly regulated countries (US/HIGH/HDE) and weakly regulated countries (non-US/LOW/LDE) is greatest (e.g., Sarbanes-Oxley Act). Furthermore, within each sub-sample a substantial amount of variation in results is now attributable to sampling error (e.g., $S_e^2/S_r^2$ ratios of 0.54 and 0.48 for US and non-US studies vis-à-vis 0.26 for the sample as a whole); together with less significant chi-square statistics, this confirms that disclosure environments across countries do partially moderate results.

(Table 8 about here)

[19] LDE countries: Austria, Bahrain, Belgium, Brazil, Denmark, Egypt, France, Germany, Hong Kong, India, Indonesia, Korea, Kuwait, Malaysia, Netherlands, Oman, Philippines, Qatar, Saudi Arabia, Singapore, Spain, Sweden Switzerland, Taiwan, and United Arab Emirates.

[20] It should be noted that while effect sizes differ markedly in magnitude, only some of them are statistically significant: US-PF, NonUS-PF, HIGH-FF, HDE-PF, LDE-PF. However, as the differences in effect sizes between disclosure environments and disclosure types are all highly significant (minimum t-statistic 13.46, untabulated two-sample T-test), my conclusions remain qualitatively unchanged.

### 5.1.3 Summary of Results

Figure 2 summarizes the key results from meta-analyzing the association between *Quantity* and CoE. Taken together, findings suggest that researchers' choice of CoE measurement does *not* explain mixed results in the disclosure literature, but it is the type of disclosure (financial vs. partial-/non-financial) as well as the disclosure setting (strongly vs. weakly regulated countries) which moderates results: CoE effects emanating from partial-/non-financial disclosure are insignificant (rejecting H1), but economically and statistically material for financial disclosure (confirming H1). Furthermore, in countries where disclosure regulation and requirements are low (non-US/LOW/LDE), investors appreciate firms' disclosure efforts to a much greater extent than in higher regulated environments (US/HIGH/HDE groups).

(Figure 2 about here)

## 5.2 Information Precision and Cost of Equity

Forty-eight (48) observations analyze the CoE effects of *Precision*, most of which relate to published work (n=42; 88%) and appear in higher-tier journals (29; 60%). The sample is strongly tilted towards US firms, with only nine observations (19%) stemming from non-US data. About one-third of observations use realized returns to proxy for CoE (REAL: 16; 33%) and the remaining two-thirds mainly apply VMB estimates (VMB: 26; 54%; RFB: 6; 13%). The vast majority of studies (41; 85%) rely on accounting/earnings quality measures for information precision, with analyst-based proxies (7; 15%) being the exception (see Table 5).

Focusing on the general conclusion of each paper, about half of all observations (n=27; 56%) confirm the negative association between *Precision* and CoE, eight studies tend to reject it (17%), and the remaining papers provide mixed/conditional results for this link (13; 27%). For instance, Ogneva (2012) shows that only after controlling for cash flow shocks in realized returns does a negative association with *Precision* exist; Kim and Qi (2010) confirm H2 after excluding low-priced firms from their sample, and Mashruwala and Mashruwala (2011) document a negative relation only in January. This qualitative assessment is consistent with meta-analytic results (shown in Table 9). The mean effect size between *Precision* and CoE is -0.048 with a 95% confidence interval between -0.142 and 0.047, illustrating that results are mixed across studies. A highly significant $\chi^2$ of 177.89 with 47 degrees of freedom along with only 27 percent of observed variance explained by sampling error ($S_e^2/S_r^2$) rejects the null of homogenous data and signposts the presence of moderating effects.

(Table 9 about here)

### 5.2.1 Measurement of Cost of Equity

As before, I divide my sample into two sub-groups according to CoE measurement (Table 9, Row II & III). Total average effect size for the REAL group is -0.014.[21] The effect size for RFB/VMB is about seven times larger ($\bar{r}$: -0.082) and almost significant at the 10% level (p-value: 0.111). The difference between the two effect sizes is highly significant (t-statistic: -165.1; untabulated two-sample T-test). Overall, this proves that the measurement of CoE has a moderating effect on results. While there seems to be no relation between *Precision* and a firm's realized returns, the association with RFB and VMB proxies is statistically and economically meaningful.[22]

### 5.2.2 Measurement of Information Precision

In a similar vein, the empirical measurement of *Precision* might explain the overall insignificant correlation with CoE ($\bar{r}$: -0.048 ± 0.095). However, irrespective of whether *Precision* is proxied by accounting quality (-0.044 ±0.085) or analyst forecasts (-0.067 ± 0.139), the relations with CoE remain insignificant (Table 9, Row IV). Moreover, results suggest that data heterogeneity stems from RFB/VMB studies, since variation across REAL results is mainly due to sampling error ($\chi^2$: 9.55, df: 15). Therefore, I focus subsequent moderator effect analyses on RFB/VMB studies.

Table 9, Row II, shows that the relation between CoE and analyst-based proxies is twice as strong ($\bar{r}$: -0.142 vs. -0.074), considerably more significant (p-value: 0.000 vs. 0.122) and less heterogonous ($\chi^2$: 9.03* vs. 83.21***) than for accounting quality-based

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[21] As the sampling error variance ($Se^2$) is larger than the observed variance ($Sr^2$), the population variance ($Sp^2$) is negative; thus, no meaningful confidence interval can be determined.

[22] The effect size between information precision and RFB proxies ($\bar{r}$: -0.100 ± 0.084) is slightly stronger than for VMB proxies ($\bar{r}$: -0.073 ± 0.103); however, as the number of RFB studies is low (n=6), a separate sub-group is not meaningful.

proxies. This stronger correlation might be explained by the fact that analyst-based proxies are more volatile measures of *Precision* than accounting quality proxies, with greater variance leading to higher correlations coefficients. For instance, Barron et al.'s (1998) AFP measure is perceived to be highly sensitive to outliers and measurement error (Barron et al., 2012, p. 21) which makes it a highly dispersed proxy for *Precision*. In contrast, Dechow and Dichev's (2002) accrual quality (AQ) metric—the most widely used measure of accounting quality—is estimated from a time-series of firm fundamentals that increases its robustness and decreases dispersion. To this extent, accounting quality studies draw a more conservative picture of the relation between *Precision* and CoE.

A sufficiently large number of accounting quality-based studies (n=41) allows for further analysis of this subset of observations.[23] Designated by a significant chi-square statistic ($\chi^2$: 83.21***, df: 26), the link between accounting quality and RFB/VMB estimates is exposed to moderator effects—REAL results, on the other hand, are unmoderated, but economically weak. As noted before, AQ metrics are a common proxy for accounting quality. Table 10, Row II, sub-samples data accordingly and shows that the relation between the AQ-metric group and CoE remains moderated ($\chi^2$: 68.04***, df: 14) and insignificant ($\bar{r}$: -0.082 ± 0.120), while the opposite is observed for non-AQ metrics—such as earnings value relevance or accounting conservatism ($\chi^2$: 13.08, df: 11; $\bar{r}$: -0.063 ± 0.020). Differently stated, as the proxies in my sample become more heterogenous, the correlation with CoE becomes less, not more, moderated which is contrary to expectations in that one may assume that studies sharing the same underlying empirical measure would also yield similar results. Therefore, the debate over whether *Precision* impacts upon CoE is in fact a debate over whether accrual quality affects CoE: results for the remaining studies, which at times use very diverse measures, corroborate the hypothesis that firms with higher *Precision* tend to enjoy lower CoE.

(Table 10 about here)

[23] Given that my sample includes only seven analyst-based studies, further in-depth analysis is not meaningful.

### 5.2.3 Summary of Results

Figure 3 reviews the main meta-analytic findings. Overall, the statistical and economic significance of the relationship between information precision and CoE tends to depend on the measurement of CoE: higher *Precision* leads to lower CoE if measured by RFB/VMB proxies, but this link is trivial in asset pricing tests and when average realized returns are used. Furthermore, a material association between RFB/VMB proxies and analyst-based as well as non-AQ metric-based studies is found. However, this relation is insignificant in studies using AQ metrics as measures of accounting quality; H2 is confirmed when non-AQ and analyst-based proxies are used for information precision and RFB/VMB proxies for CoE but rejected when AQ and REAL proxies are applied.

(Figure 3 about here)

## 5.3 Information Asymmetry and Cost of Equity

Twenty-eight (28) observations in my sample examine the link between *Asymmetry* and CoE of which most relate to published work (n=25; 89%) and appear in higher-tier journals (24; 86%). The sample is strongly tilted towards US studies, with only four observations (14%) relying on non-US data. Three-quarters of observations apply *ex post* estimates for CoE (REAL: 21; 75%) and the remainder exclusively use VMB measures (VMB: 7; 25%). The vast majority of studies (24; 86%) utilize market microstructure proxies (i.e., PIN scores, bid-ask spreads), whereas non-microstructure estimates (e.g., analyst-based proxies) are rarely used (see Table 5).

As noted above, a meaningful meta-analysis for the link between *Asymmetry* and CoE is not possible. Therefore, proceeding analyses focus on the general conclusion of each paper. Figure 4, Panel A, shows that about half of all observations confirm the positive association between *Asymmetry* and CoE (n=16; 57%), four observations (14%) tend to reject it, and eight observations (29%) provide mixed/conditional results. In particular, the level of market competition appears to be an important conditioning variable in empirical settings, given that *Asymmetry* effects tend to vanish as markets become more competitive (e.g., Akins, Jeffrey, and Verdi (2012), Armstrong, Core, Taylor, and Verrecchia (2011), and Luong, Nguyen, and Yin (2011)). Furthermore, findings in

Eleswarapu and Reinganum (1993) and Kang (2010) indicate the existence of January-effects.

(Figure 4 about here)

### 5.3.1 Measurement of Cost of Equity

Sub-sampling observations according to CoE measurement reveals some interesting points (see Figure 4, Panel B and C). First, the literature mainly uses realized returns to proxy for firms' CoE (REAL: 21; 75%), with seven observations (25%) relying on VMB estimates, and none using traditional RFB ones. The fact that risk factor-based models (such as the CAPM) derive from the assumption of homogenous expectations between investor groups and hence, by definition "there is no role for accounting to reduce the information asymmetry" (Shevlin, 2013, p. 466), seems to justify the non-representation of RFB proxies in extant studies. Second—and more importantly—there is notable variation in the conclusions reached by REAL studies (reject: 14%; mixed: 38%; confirm: 48%), but findings are rather uniform when VMB proxies are used (reject: 14%; confirm: 86%). This suggests that researchers' choice of CoE measurement impacts the conclusions reached regarding the CoE effects of *Asymmetry* in that VMB studies generally confirm H3, while REAL studies are more likely to reject it.

Given that realized returns tend to be noisy proxies of CoE (Chen et al. (2013), Fama and French, 1997, and Vuolteenaho (2002)), one might argue that greater weight should be placed on studies applying VMB (i.e., implied cost of capital) estimates. In other words, the reason why "only" 48 percent of REAL studies confirm the positive association between *Asymmetry* and CoE might stem from imprecise CoE estimates, which leads to low power tests (e.g. Wang (2015)). While convincing evidence exists that VMB proxies show greater validity than realized return-based proxies (e.g., Botosan and Plumlee (2005), Botosan et al. (2011), and Lee et al. (2010, 2015)), those estimates are not impeccable either. Beyond the issue of lacking estimates for young, small and financially-distressed firms due to coverage bias by analysts (e.g., Diether, Malloy, and Scherbina (2002), Hong, Lim, and Stein (2000), and La Porta (1996)), it is the problem of upward-biased implied cost of capital (ICC) estimates—due to optimistic analyst forecasts (e.g., Dugar and Nathan (1995), Francis and Philbrick (1993), and

McNichols and O'Brien (1997))—which raises particular concerns. For example, Hwang et al. (2013) conclude that "as long as the [ICC] estimates are derived from analysts' earnings forecasts, potential measurement errors in [ICC] estimates could remain and influence […] findings." Therefore, the authors call for "more efforts to fine-tune [ICC] measures" (p. 165). Model-based ICC estimates might be one remedy to overcome these analyst-related deficiencies in future work (e.g., Hou, van Dijk, and Zhang (2012), and Li and Mohanram (2014)).

### 5.3.2 Measurement of Information Asymmetry

As most studies in my sample rely on market microstructure-based proxies to measure information asymmetry (n=24; 86%), I concentrate subsequent analyses on this subset of observations. Figure 5 shows that PIN scores are most widely used (17; 71%) in the literature, followed by bid/ask spreads operated in some studies (7; 29%). None of the spread-based studies reject the direct link between *Asymmetry* and CoE (Figure 5, Panel C) which suggests that higher bid/ask spreads indicate greater information asymmetry and can induce higher CoE. In contrast, the association between PIN scores and CoE is somewhat debated (reject: 24%, mixed: 18%, confirm: 59%): Mohanram and Rajgopal (2009, p. 241) conclude that "there is not much evidence [that] PIN is a source of priced information risk" and Duarte and Young (2009) argue that it is the illiquidity component of PIN which explains the positive relation with CoE, and not the *Asymmetry* part of it. However, the majority of studies in my sample confirm the negative CoE effects arising from asymmetric information (Figure 5, Panel B). Together with new evidence from longer sampling periods (e.g., Aslan, Easley, Hvidkjaer, and O'Hara (2011), and Brennan, Huh, and Subrahmanyam (2016)) and improved estimation techniques (e.g., Easley, López de Prado, and O'Hara (2012), and Hwang, Lee, Lim, and Park (2013)), this substantiates the proposition of PIN being an important driver of CoE.[24]

(Figure 5 about here)

[24] See also Boehmer, Grammig, and Theissen (2007), Yan and Zhang (2012), and William Lin and Ke (2011) for a discussion on how to improve PIN score measurement.

### 5.3.3 Summary of Results

Figure 6 summarizes key results from the analysis of information asymmetry with CoE and shows that evidence is strongest for VMB proxies and bid-ask spreads, but somewhat mixed for REAL proxies and PIN scores. Overall, the majority of studies find a positive *Asymmetry*-CoE relation which corroborates the conjecture of informational disparity between investor groups causing an increase in firms' CoE (confirming H3). However, recent analytical and empirical evidence demonstrates that high levels of market competition tend to subdue these *Asymmetry* effects. Specifically, Akins et al. (2012), Armstrong et al. (2011) and Luong et al. (2011) show that—consistent with the analytical model of Lambert et al. (2012)—the significance of *Asymmetry* on CoE declines as market competition increases; that is, in perfectly liquid markets, in which both informed and uninformed investors act as price takers, asymmetric information has no material effect on firms' CoE. These findings put forward market competition as an important conditioning variable in future research.[25]

(Figure 6 about here)

## 5.4 Additional Analysis

To address concerns of publication bias (Møller & Jennions, 2001), I test for differences in meta-analytic results between higher-tier and lower-tier journals. Table 11 reports findings for the link between *Quantity* and CoE and shows that there is no clear pattern regarding the differences in average effect sizes between the two groups: higher-tier journals report a stronger effect size when RFB/VMB proxies are being used (high: -0.081; low: -0.055), while lower-tier journals report a stronger effect size for REAL proxies (-0.020; -0.158). Similarly, higher-tier studies find stronger CoE effects for financial disclosure (-0.119; -0.044), while lower-tier studies report a stronger relation with partial-financial disclosure (-0.038; -0.138)—average effect sizes for non-financial disclosure are alike (-0.061; -0.040). Comparable patterns are observed for the link between *Precision* and CoE (see Table 12). For instance, when measuring CoE by

[25] Common proxies for market competition include: investor concentration (Akins et al., 2012), institutional ownership (Luong et al., 2011) and number of shareholders (Armstrong et al. (2011), Barron et al. (2012)).

RFB/VMB proxies, total average affect size is larger in higher-tier journals ($\bar{r}$: -0.097) than in lower-tier ones (-0.067); in contrast, when focusing on realized return-based studies, total average effect size is larger for lower-tier (-0.019) vis-à-vis higher-tier publications (-0.014). However, for both links results in higher-tier journals are slightly more heterogenous than in lower-tier ones—which can be inferred from more significant chi-squares, lower $S_e^2/S_r^2$ ratios and wider confidence intervals—indicating that the CoE effects of *Quantity* and *Precision* are discussed more controversially in higher-tier outlets.

As a further robustness test, I follow Ahmed, Chalmers, and Khlif (2013) and calculate for all significant results a "fail-safe" N statistic that estimates the number of unpublished studies reporting null results required to reduce the mean effect size to a specified criterion.[26] In particular, I am examining how many studies are necessary to reduce observed effect sizes from the meta-analyses to a hypothetical effect size of just below zero. Using a criterion of -0.01, it requires approximately 40 studies to revert the negative association between financial disclosure and CoE and about 73 studies to change the overall negative relation between *Precision* and VMB/RFB proxies, with 23 (18) studies needed to alter results when *Analyst* (non-AQ*)* proxies are being used. Taken together, these additional tests suggest that my main findings tend to be free of publication bias and unaffected by the file drawer problem.

(Table 11 about here)

(Table 12 about here)

# 6 Discussion of Results and Conclusion

This paper provides a quantitative review of the literature examining the effect of idiosyncratic information on firms' CoE capital. For the links of *Quantity* and *Precision* with CoE I report meta-analytic results, and for the link with *Asymmetry* I provide de-

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[26] The fail-safe N statistic is calculated as: $K_0 = K\left[\frac{\bar{r}_k}{\bar{r}_0} - 1\right]$ where $K_0$ is the number of unpublished studies required to affect conclusion reached (i.e., fail-safe N), $K$ is the total number of studies included in the meta-analysis, $\bar{r}_k$ is the reported mean effect size, $\bar{r}_0$ is the criterion effect size specified by the research (Orwin, 1983).

scriptive statistics only due to data constraints. In total, I review the results of 113 unique papers and my findings suggest that the association between firm-specific information and CoE is subject to moderate effects as indicated by insignificant average effect sizes (*Quantity*: -0.066 ± 0.124; *Precision*: -0.048 ± 0.095), and a notable number of studies (29%) that only find conditional results for the link between *Asymmetry* and CoE.

The empirical measurement of both CoE and information attributes partially explains these mixed results. First, findings for the link between *Quantity* and CoE depend on disclosure type (financial vs. partial-/non-financial) and disclosure settings insofar as firms in comparatively weakly regulated countries tend to enjoy two to four times greater CoE benefits from more expansive disclosure—depending on the type of disclosure—than firms in highly regulated countries such as the US or the UK. Second, the conjectured negative relationship between *Precision* and CoE is only significant in studies using analyst-based and non-accrual quality proxies for *Precision* and RFB/VMB proxies for CoE. That is, the link between information precision and CoE seems trivial in asset pricing tests (REAL proxies) or when accrual quality metrics are used. Third, almost all VMB studies confirm the positive association between *Asymmetry* and CoE (86%), but there is notable variation in the conclusions reached by REAL studies (reject: 14%; mixed: 38%; confirm: 48%).

*Impact of Endogeneity.* Endogeneity is a major challenge in the extant literature (e.g., Core (2001)) and offers an alternative explanation for mixed meta-analytic findings. In particular, simultaneity and reverse causality creates difficulties when examining the theoretically negative relation between *Quantity*/*Precision* and CoE: firms disclose more or better information to lower their CoE (i.e., negative correlation), but only firms with high CoE decide to do so (i.e., positive correlation). Hence, endogeneity can lead to an insignificant relation between information quality and firms' CoE (e.g., Balakrishnan, Billings, Kelly, and Ljungqvist (2014)). To this extent, the insignificance of some results might be explained by the fact that data used in the meta-analyses are typically from correlation matrices and, therefore, not incorporating methods used by the studies in my sample to address endogeneity.

*CoE Measurement.* VMB measures are most frequently used in the literature (e.g., 60 percent of all 138 observations use such proxies in my sample), followed by asset pricing tests and realized returns (REAL) in second place (31%) and RFB estimates in third (9%). Extant findings, therefore, hinge on the validity of the CoE measures applied: results are only as valid as the proxies used to attain them. In other words, the commonly found negative relationship between higher information quality and VMB proxies might be a spurious one (i.e., better information may "simply" reduce optimism in analyst forecasts which lowers VMB estimates mechanically) and noise in realized returns may explain the generally insignificant relationship in REAL studies (e.g., McInnis (2010), and Ogneva (2012)).

These issues of CoE measurement raise the question of how to weigh existing evidence. Given that valuation model-based estimates tend to be more valid measures of CoE than realized return-based proxies (e.g., Botosan and Plumlee (2005), Botosan et al. (2011), and Lee et al. (2010, 2015)), one might place greater weight on the conclusions reached in VMB studies: firms with better corporate information environments are likely to enjoy lower CoE than otherwise identical firms. However, analyst-based ICC estimates tend to be upward-biased, leading to distorted results (e.g., Easton and Monahan (2005, 2016), and Easton and Sommers (2007)). Moreover, young, small and financially-distressed firms are rarely covered by security analysts (e.g., Diether et al. (2002), Hong et al. (2000), and La Porta (1996)), biasing ICC samples towards larger and more established firms.

While analyst forecast bias can be corrected for (e.g., Guay, Kothari, and Shu (2011), Larocque (2013), and Mohanram and Gode (2013)), the problem of sampling bias remains in analyst-based ICC studies. This poses a trade-off for researchers to use either a *less* representative sample with *more* valid CoE proxies (VMB) or a *more* representative sample with *less* valid return estimates (REAL). To this extent, VMB findings are not necessarily generalizable towards smaller and younger firms, and REAL study results may be confounded by cash-flow and discount-rate news. Recent advancements in model-based ICC estimates might help overcome this predicament in future work because these estimates are analyst-independent—removing forecast bias—and calculated from firms' current accounting information only, thus ensuring representative samples (e.g., Hou et al. (2012), and Li and Mohanram (2014)).

*Information Quality Measurement.* The literature uses several different proxies for firms' information attributes and results vary depending on which proxy is used (e.g., AQ vs. non-AQ; PIN vs. SPREAD-based studies). However, even when identical information proxies are applied, disagreement in the literature remains (see, for example, Core et al. (2008) and Mohanram and Rajgopal (2009) for a discussion on the pricing of accrual quality and PIN scores). Measurement error in the proxies for *Precision*, *Asymmetry* and *Quantity* might cause these inconsistent results and one way to address it is to improve the empirical soundness of the respective proxies (e.g., McNichols (2002) AQ metric modification of the Dechow-Dichev (2002) model; Brown and Hillegeist (2007) and Hwang et al. (2013) PIN score modification of the Easley et al. (1996, 1997) model). However, despite such improvements, no single proxy can be entirely free of measurement error. Thus, another approach to deal with this errors-in-variable problem is to operationalize more elaborate research designs. In this respect, further work along the lines of Verdi (2005), who uses principal component analysis to control for noise in information proxies, seems beneficial to increase empirical robustness of results.

*General Implications of Findings.* Extant evidence is (yet) insufficient to support idiosyncratic information as a separate risk factor in asset pricing models (i.e., rigorous asset pricing test as in Core et al. (2008) and Mohanram and Rajgopal (2009) tend to refute the possibility of an information risk factor). However, evidence is ample enough to confirm the hypothesis of better information quality leading to lower CoE (e.g., Core et al. (2008) themselves find that better accrual quality leads to lower market beta which is equal to lower CoE). While at first glance an antithesis, this conclusion is consistent with economic theory that corroborates a negative relationship between idiosyncratic information and CoE, but questions if it impacts CoE directly (e.g., Easley and O'Hara (2004), and Lambert et al. (2012)) or only indirectly through other risk factors such as market beta (e.g., Hughes et al. (2007), and Lambert et al. (2007)). My findings also suggest important implications for practice: firms can lower their CoE if they release more value-relevant information to investors (e.g., committing to more expansive disclosure), provide information of higher precision (e.g., following stricter reporting standards), and disseminate information more widely between investor groups (e.g., promoting investor relations). However, these benefits are likely to be attenuated in countries where strong regulation and transparency requirements establish *ex ante* high quality corporate information environments.

It should also be noted that the extant literature is silent on the relative importance of *Precision*, *Asymmetry* and *Quantity* as determinates of firms' CoE; that is, which of the three attributes has comparatively greater CoE relevance remains unanswered by current studies. Therefore, to resolve the debate about the market pricing of idiosyncratic information empirically, it seems necessary to extend prevailing research designs—which examine the impact of one information proxy on one CoE proxy at a time—towards a comprehensive methodology that allows for simultaneously examining the different information attributes and CoE measures within one empirical model. Such an approach might help disentangle the underlying complexity between idiosyncratic information and firms' CoE. A first promising step in this direction has been taken by Bhattacharya et al. (2012).

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# Appendix: Journal Index

| Journal | Abbreviation | ABS 2015 |
|---|---|---|
| Academy of Taiwan Business Management Review | ATBMR | n/a |
| Accounting in Europe | AIE | 2 |
| **Accounting Review** | **TAR** | **4** |
| **Accounting, Organizations and Society** | **AOS** | **4** |
| Advanced Science Letters | ASL | n/a |
| Advances in Accounting, incorporating Advances in International Accounting | AIA | 2 |
| Applied Economics | AE | 2 |
| Asian Journal of Business and Accounting | AJBA | n/a |
| Asian Review of Accounting | ARA | 2 |
| Asia-Pacific Journal of Accounting & Economics | APJAE | 2 |
| Asia-Pacific Journal of Financial Studies | APJFS | n/a |
| Australian Accounting Review | AAR | 2 |
| Australian Journal of Management | AJM | n/a |
| Business Research | BR | n/a |
| China Finance Review International | CFRI | 1 |
| **Contemporary Accounting Research** | **CAR** | **4** |
| Corporate Social Responsibility and Environmental Management | CSREM | 1 |
| Emerging Markets Finance and Trade | EMFT | n/a |
| **European Accounting Review** | **EAR** | **3** |
| European Management Journal | EMJ | 2 |
| Global Journal of Business Research | GJBR | n/a |
| Industrial Management and Data Systems | IMDS | 2 |
| **International Business Review** | **IBR** | **3** |
| **International Journal of Accounting** | **IJA** | **3** |
| **International Journal of Forecasting** | **IJF** | **3** |
| International Review of Economics and Finance | IREF | 2 |
| **International Review of Financial Analysis** | **IRFA** | **3** |
| **Journal of Accounting and Economics** | **JAE** | **4** |
| **Journal of Accounting and Public Policy** | **JAPP** | **3** |
| **Journal of Accounting Research** | **JAR** | **4** |
| **Journal of Accounting, Auditing and Finance** | **JAAF** | **3** |
| Journal of Applied Accounting Research | JAAR | 2 |
| **Journal of Banking and Finance** | **JBF** | **3** |
| Journal of Business | JB | n/a |
| **Journal of Business Finance and Accounting** | **JBFA** | **3** |
| Journal of Business, Economics and Finance | JBEF | n/a |
| **Journal of Corporate Finance** | **JCF** | **4** |
| Journal of Economics, Finance and Administrative Science | JEFA | n/a |
| **Journal of Empirical Finance** | **JEF** | **3** |

*Table continued next page.*

## Journal Index (cont.)

| Journal | Abbreviation | ABS 2015 |
|---|---|---|
| **Journal of Finance** | **JF** | **4** |
| **Journal of Financial and Quantitative Analysis** | **JFQA** | **4** |
| **Journal of Financial Economics** | **JFE** | **4** |
| Journal of Intellectual Capital | JIC | 2 |
| **Journal of International Financial Markets, Institutions and Money** | **JIFMIM** | **3** |
| Journal of Multinational Financial Management | JMFM | 2 |
| **Journal of Risk and Insurance** | **JRI** | **3** |
| Management Decision | MD | 2 |
| **Management Science** | **MS** | **4** |
| Management Science and Engineering | MSE | n/a |
| Managerial and Decision Economics | MDE | 2 |
| Managerial Finance | MF | 1 |
| North American Journal of Economics and Finance | NAJEF | 2 |
| Pacific Accounting Review | PAR | 1 |
| Quarterly Journal of Finance | QJF | 1 |
| Review of Accounting and Finance | RAF | 2 |
| **Review of Accounting Studies** | **RAST** | **4** |
| **Review of Finance (European Finance Review)** | **RF** | **4** |
| **Review of Quantitative Finance and Accounting** | **RQFA** | **3** |
| SSRN | SSRN | n/a |

*Notes: Journals in bold are categorised as high-tier journals in this study. Ranking follows the Academic Journal Guide 2015 (ABS).*

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**Table 1: Attributes and Keywords**

| **Attributes** | **Keywords** |
|---|---|
| Information Quantity | ▪ information quantity/amount<br>▪ information/estimation risk<br>▪ mandatory/voluntary disclosure<br>▪ financial/non-financial disclosure<br>▪ age/listing/operating history<br>▪ media/press coverage<br>▪ firm/company prominence |
| Information Precision | ▪ information precision/accuracy/quality<br>▪ financial reporting quality<br>▪ accounting quality<br>▪ earnings quality/management<br>▪ earnings attributes<br>▪ accrual quality<br>▪ analyst forecast<br>▪ security analyst<br>▪ analyst forecast precision/accuracy/dispersion<br>▪ earnings/analyst characteristic<br>▪ earnings persistence/predictability/smoothness/value relevance/timeliness/conservatism |
| Information Asymmetry | ▪ information asymmetry/dissemination/dispersion<br>▪ informational dis/advantages<br>▪ un/informed investor<br>▪ public/private information<br>▪ probability of informed trading/PIN<br>▪ bid-ask spread<br>▪ investor concentration/competition<br>▪ market liquidity<br>▪ firm-specific information<br>▪ idiosyncratic information |
| Cost of Equity | ▪ cost of equity<br>▪ cost of capital<br>▪ implied cost of capital<br>▪ expected rate of return<br>▪ required rate of return<br>▪ discount rate<br>▪ weighted cost of capital |

*The table shows for each information attribute (and cost of equity) the respective keywords searched for in several databases and journals.*

**Table 2: Information Quantity on CoE – Description of Studies Included in the Meta-Analysis**

| Study | Journal* | Country† | US?† | Disc. Env.€ | Disc. Reg. Score$ | No. of firms§ | No. of firm-years‡ | Sampling Period | DV: CoE¥ | IV: Quantity£ | Disc. Type£ | Disc. Metric£ | Direct Link? | Effect size (Pearson's *r* coefficient) | Source of Information |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Al Guindy (2016) | SSRN | US | Y | HDE | 1.00 | 1,232 | 8,626 | 2007-2013 | VMB | Disc. | NF | Dummy | Confirm | -0.0870 | Table 5, p. 30 |
| Al Guindy (2016) | SSRN | US | Y | HDE | 1.00 | 54 | 381 | 2007-2013 | VMB | Disc. | FF | Dummy | Confirm | -0.1008 | Table 6, p. 31 |
| Al-Hadi, Taylor, and Hossain (2015) | JMFM | 6 Count. | N | LDE | n/a | 141 | 705 | 2007-2011 | VMB | Disc. | PF | SCI | Confirm | -0.0160 | Table 2, p. 80 |
| Bachoo et al. (2013) | AAR | AUS | N | LDE | 0.75 | 150 | 450 | 2003-2005 | VMB | Disc. | NF | Dummy | Confirm | -0.0157 | Table 3, p. 78 |
| Baginski and Rakow (2012) | RAST | US | Y | HDE | 1.00 | 1,355 | 1,355 | 2004 | VMB | Disc. | FF | SCI | Confirm | -0.1164 | Table 4, p. 299 |
| Blanco, Garcia Lara, and Tribo (2015) | JBFA | US | Y | HDE | 1.00 | 1,667 | 10,002 | 2001-2006 | VMB | Disc. | PF | SCI | Confirm | -0.1281 | Table 6, p. 391 |
| Blanco et al. (2015) | JBFA | US | Y | HDE | 1.00 | 1,667 | 8,502[b] | 2001-2006 | REAL | Disc. | PF | SCI | Confirm | -0.0314 | Table 10, p. 398 |
| Botosan (1997) | TAR | US | Y | HDE | 1.00 | 122 | 122 | 1990 | VMB | Disc. | PF | SCI | Confirm | -0.1430 | Table 7, p. 342 |
| Botosan and Plumlee (2002) | JAR | US | Y | HDE | 1.00 | 246 | 2,706 | 1986-1996 | VMB | Disc. | PF | EXI | Mixed | 0.0110 | Table 4, p. 34 |
| Boujelbene and Affes (2013) | JEFA | FR | N | LDE | 0.75 | 102 | 102 | 2009 | RFB | Disc. | NF | SCI | Confirm | -0.2180 | Table 4, p. 50 |
| Campbell et al. (2014) | RAST | US | Y | HDE | 1.00 | 2,048 | 8,193 | 2005-2008 | REAL | Disc. | PF | SCI | Confirm | -0.0292 | Table 8, p. 436 |
| Cao et al. (2017) | RAST | 31 Count. | B | n/a | 0.84 | 6,309 | 37,856 | 2004-2009 | VMB | Disc. | FF | Dummy | Confirm | -0.1500 | Table 2, p. 14 |
| Chen, Wei, and Chen (2003) | SSRN | 9 Count. | N | LDE | 0.87 | 273 | 545 | 2000-2001 | VMB | Disc. | PF | EXI | Confirm | -0.1400 | Table 6, p. 391 |
| Cheng et al. (2006) | RQFA | US | Y | HDE | 1.00 | 348 | 348 | 2001-2002 | VMB | Disc. | FF | EXI | Confirm | -0.0500 | Table 2, p. 193 |
| Chien and Lu (2015) | IMDS | US | Y | HDE | 1.00 | 4,122 | 16,488 | 2009-2012 | RFB | Disc. | NF | SCI | Confirm | -0.0090 | Table 4, p. 515 |
| Clarkson et al. (2013) | JAPP | US | Y | HDE | 1.00 | 98 | 195 | 2003, 2006 | VMB | Disc. | NF | SCI | Reject | 0.1096 | Table 4. p. 423 |
| Core et al. (2015) | EAR | 35 Count. | B | n/a | 0.86 | 3,347 | 50,201 | 1990-2004 | VMB | Disc. | PF | SCI | Confirm | -0.0083 | Table 3, p. 14 |
| Core et al. (2015) | EAR | 35 Count. | B | n/a | 0.86 | 3,347 | 50,201 | 1990-2004 | REAL | Disc. | PF | SCI | Confirm | -0.0030 | Table 4, p. 18 |
| Déjean and Martinez (2009) | AIE | FR | N | LDE | 0.75 | 112 | 112 | 2006 | RFB | Disc. | NF | SCI | Reject | 0.1450 | Table 5, p. 73 |
| Dhaliwal et al. (2011) | TAR | US | Y | HDE | 1.00 | 795 | 11,925 | 1993-2007 | VMB | Disc. | NF | Dummy | Mixed | -0.0297 | Table 4, p. 76 |
| Dhaliwal et al. (2014) | JAPP | 31 Count. | B | n/a | 0.83 | 6,093 | 79,212 | 1995-2007 | VMB | Disc. | NF | Dummy | Confirm | -0.0700 | Table 3, p. 341 |
| Elzahar, Hussainey, Mazzi, and Tsalavoutas (2015) | IRFA | UK | N | HDE | 0.83 | 90 | 448 | 2006-2010 | VMB | Disc. | FF | SCI | Confirm | -0.1695 | Table 7, p. 106 |
| Elzahar et al. (2015) | IRFA | UK | N | HDE | 0.83 | 90 | 448 | 2006-2010 | VMB | Disc. | NF | SCI | Reject | -0.0378 | Table 7, p. 106 |
| Embong, Mohd- Saleh, and Hassan (2012) | ARA | MY | N | LDE | 0.92 | 135 | 406 | 2004-2006 | VMB | Disc. | PF | SCI | Mixed | -0.1430 | Table 2, p. 126 |

*Table continued next page.*

**Table 2: Information Quantity on CoE – Description of Studies Included in the Meta-Analysis (cont.)**

| Study | Journal* | Country† | US?† | Disc. Env.€ | Disc. Reg. Score$ | No. of firms§ | No. of firm-years‡ | Sampling Period | DV: CoE¥ | IV: Quantity£ | Disc. Type£ | Disc. Metric£ | Direct Link? | Effect size (Pearson's *r* coefficient) | Source of Information |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Espinosa and Trombetta (2007) | JBFA | SP | N | LDE | 0.50 | 50 | 250 | 1998-2002 | VMB | Disc. | PF | EXI | Mixed | -0.2000 | Table 4, p. 1384 |
| Eugster (2014) | SSRN | CH | N | LDE | 0.67 | 104 | 1,039 | 1999-2008 | VMB | Disc. | PF | EXI | Mixed | -0.2260 | Table 4, p. 40 |
| Evans (2016) | CAR | US | Y | HDE | 1.00 | 187 | 935 | 2003-2007 | VMB | Disc. | FF | SCI | Mixed | 0.0440 | Table 1, pp.1147-8 |
| Feng, Li, and Gu (2009) | SSRN | US | Y | HDE | 1.00 | 335 | 4,024 | 1995-2006 | VMB | Disc. | FF | SCI | Mixed | -0.0343 | Table 4, pp. 30-1 |
| Francis, Khurana, et al. (2005) | TAR | 23 Count. | N | n/a | 0.69 | 137 | 274 | 1991, 1993 | VMB | Disc. | PF | EXI | Confirm | -0.1450 | Table 7, p. 1154 |
| Francis et al. (2008) | JAR | US | Y | HDE | 1.00 | 677 | 677 | 2001 | VMB | Disc. | PF | SCI | Mixed | -0.0381 | Table 4, p. 79 |
| Fu et al. (2012) | JAE | US | Y | HDE | 1.00 | 333 | 7,654 | 1951-1973 | REAL | Disc. | NF | SCI | Confirm | -0.0600 | Table 3, p. 139 |
| Fu et al. (2012) | JAE | US | Y | HDE | 1.00 | 333 | 7,654 | 1951-1973 | RFB | Disc. | NF | SCI | Confirm | -0.0500 | Table 3, p. 139 |
| García-Sánchez and Noguera-Gámez (2017) | IBR | 27 Count. | B | n/a | 0.72 | 659 | 3,294 | 2009-2013 | VMB | Disc. | PF | Dummy | Confirm | -0.0620 | Table 5, p. 965 |
| Gietzmann and Ireland (2005) | JBFA | UK | N | HDE | 0.83 | 30 | 301 | 1993-2002 | VMB | Disc. | PF | SCI | Mixed | -0.1340 | Table 2c, p. 625 |
| Grüning (2011) | BR | DE | N | LDE | 0.42 | 361 | 361 | 2006 | REAL | Disc. | PF | EXI | Confirm | -0.1580 | Table 4, p. 58 |
| Hail (2002) | EAR | CH | N | LDE | 0.67 | 73 | 73 | 1997 | VMB | Disc. | PF | EXI | Confirm | -0.4780 | Table 5, p. 761 |
| Healy et al. (1999) | CAR | US | Y | HDE | 1.00 | 37 | 408 | 1980-1990 | REAL | Disc. | PF | EXI | Confirm | -0.1034 | Table 6, p. 504 |
| Khlif, Samaha, and Azzam (2015) | JAAR | EG | N | LDE | 0.50 | 73 | 292 | 2006-2009 | RFB | Disc. | PF | SCI | Confirm | -0.2730 | Table 4, p. 44 |
| Kim and Shi (2011) | JAPP | US | Y | HDE | 1.00 | 1,066 | 3,198 | 2003-2005 | VMB | Disc. | FF | Dummy | Mixed | 0.0148 | Table 5, p. 360 |
| Kothari et al. (2009) | TAR | US | Y | HDE | 1.00 | 223 | 1,338[a] | 1996-2001 | RFB | Disc. | PF | SCI | Confirm | -0.0313 | Table 3, p. 1658 |
| Kristandl and Bontis (2007) | JIC | 4 Count. | N | LDE | 0.46 | 95 | 95 | 2004 | VMB | Disc. | PF | SCI | Mixed | 0.0315 | Table 6, p. 587 |
| La Rosa and Liberatore (2014) | EMJ | 8 Count. | N | n/a | 0.60 | 62 | 309 | 2005-2009 | VMB | Disc. | PF | SCI | Reject | 0.0560 | Table 10, p. 816 |
| Lopes and de Alencar (2010) | IJA | BR | N | LDE | 0.25 | 55 | 276 | 1998, 2000/02/04/05 | VMB | Disc. | PF | SCI | Confirm | -0.2900 | Table 3, p. 454 |
| Mangena et al. (2016) | JAAF | UK | N | HDE | 0.83 | 125 | 125 | 2004 | VMB | Disc. | FF | SCI | Confirm | -0.2500 | Table 3, p. 12 |
| Mangena et al. (2016) | JAAF | UK | N | HDE | 0.83 | 125 | 125 | 2004 | VMB | Disc. | NF | SCI | Confirm | -0.3440 | Table 3, p. 12 |
| Ng and Rezaee (2015) | JCF | Global | B | n/a | n/a | 598 | 13,745 | 1991-2013 | VMB | Disc. | NF | SCI | Confirm | -0.0300 | Table 3, pp. 138-9 |
| Ogneva et al. (2007) | TAR | US | Y | HDE | 1.00 | 2,021 | 2,021 | 2004 | VMB | Disc. | NF | Dummy | Reject | 0.0127 | Table 2, pp.1268-9 |

*Table continued next page.*

**Table 2: Information Quantity on CoE – Description of Studies Included in the Meta-Analysis (cont.)**

| Study | Journal* | Country† | US?† | Disc. Env.€ | Disc. Reg. Score$ | No. of firms§ | No. of firm-years‡ | Sampling Period | DV: CoE¥ | IV: Quantity£ | Disc. Type£ | Disc. Metric£ | Direct Link? | Effect size (Pearson's *r* coefficient) | Source of Information |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Orens, Aerts, and Lybaert (2009) | MD | 4 Count. | N | LDE | 0.55 | 223 | 223 | 2002 | VMB | Disc. | NF | SCI | Confirm | -0.1313 | Table 4, pp.1547-8 |
| Orens, Aerts, and Cormier (2010) | JBFA | 7 Count. | B | n/a | 0.84 | 668 | 668 | 2002 | VMB | Disc. | NF | SCI | Confirm | -0.2720 | Table 5, p. 1076 |
| Orens, Aerts, and Lybaert (2013) | RAF | 4 Count. | N | LDE | 0.52 | 217 | 217 | 2002 | VMB | Disc. | NF | SCI | Confirm | -0.1150 | Table 4, p. 139 |
| Paugam and Ramond (2015) | JBFA | FR | N | LDE | 0.75 | 445 | 445 | 2009 | VMB | Disc. | FF | SCI | Confirm | -0.1112 | Table 4, p. 606 |
| Plumlee et al. (2015) | JAPP | US | Y | HDE | 1.00 | 79 | 474 | 2000-2005 | VMB | Disc. | NF | SCI | Confirm | -0.0150 | Table 3, p. 351 |
| Poshakwale and Courtis (2005) | MDE | Global | B | n/a | n/a | 27 | 135 | 1995-1999 | VMB | Disc. | PF | SCI | Confirm | -0.3410 | Table 4, p. 438 |
| Reverte (2012) | CSREM | SP | N | LDE | 0.50 | 19 | 114 | 2003-2008 | VMB | Disc. | NF | EXI | Confirm | -0.2388 | Table 4, p. 263 |
| Richardson and Welker (2001) | AOS | CA | N | HDE | 0.92 | 108 | 324 | 1990-1992 | VMB | Disc. | FF | EXI | Confirm | -0.0460 | Table 2, p. 604 |
| Richardson and Welker (2001) | AOS | CA | N | HDE | 0.92 | 108 | 324 | 1990-1992 | VMB | Disc. | NF | EXI | Reject | 0.0110 | Table 2, p. 604 |
| Saini and Herrmann (2012) | SSRN | US | Y | HDE | 1.00 | 87 | 87 | 2005 | VMB | Disc. | PF | SCI | Confirm | -0.0770 | Table 2, p. 42 |
| Tohang and Hutagaol-Martowidjojo (2015) | ASL | ID | N | LDE | 0.50 | 29 | 58 | 2010-2011 | VMB | Disc. | PF | SCI | Confirm | -0.2210 | Table 2, p. 901 |
| Wu et al. (2014) | EMFT | TW | N | LDE | 0.75 | 121 | 482 | 2007-2010 | VMB | Disc. | NF | Dummy | Confirm | -0.0930 | Table 3, p. 113 |
| Xiao-feng, Wei-ling, and Ming-yi (2006) | MSE | CH | N | LDE | 0.67 | 102 | 102 | 2005 | VMB | Disc. | PF | SCI | Confirm | -0.5200 | Table 4, p. 1449 |
| Xu (2009) | GJBR | US | Y | HDE | 1.00 | 212 | 212 | 1996 | VMB | Disc. | PF | EXI | Mixed | -0.0300 | Table 3, p. 21 |
| Zhao, Davis, and Berry (2009) | RAF | US | Y | HDE | 1.00 | 255 | 255 | 2000 | VMB | Disc. | NF | Dummy | Confirm | -0.1529 | Table 9, p. 274 |

*Notes:* * Journal names along with their ABS 2015 ranking are shown in the appendix.* † *AU: Australia; BR: Brazil; CH: Switzerland; CA: Canada: DE: Germany; EG: Egypt; FR: France; ID: Indonesia; MY: Malaysia; SP: Spain; TW: Taiwan; UK: United Kingdom; US: United States; Studies focusing on US firms only are denoted (Y), non-US studies (N) and studies using inseparably both US and non-US firms in their sample (B).* $ *Disc. Reg.: Disclosure regulation score from La Porta et al. (2006); in the case of multi-country studies scores are a weighted average by number of firm-years per country.* § *Number of firms is approximated as number of firm-years divided by number of sample years.* ‡ *When multiple samples are selected for one study, average sample size is reported.* ¥ *REAL: realised-return, RFB: risk factor-based, VMB: valuation model-based cost of equity proxy.* £ *Disc.: Disclosure; Disclosure Types: Full-financial (FF), part-financial (PF), non-financial (NF) disclosure; Disclosure Metrics: Self-constructed index (SCI), external third-party index (EXI), binary dummy variable (Dummy).* **a** *Converted firm-quarters into firm-years.* **b** *Converted firm-months into firm-years.*

**Table 3: Information Precision on CoE – Description of Studies Included in the Meta-Analysis**

| Study | Journal[*] | Country[†] | No. of firms[§] | No. of firm-years[‡] | Sampling Period | DV: CoE[¥] | IV: Precision[£] | Direct Link? | Effect size (Pearson's *r* coefficient) | Source of Information |
|---|---|---|---|---|---|---|---|---|---|---|
| Artiach and Clarkson (2014) | AJM | US | 196 | 3,138 | 1985-2000 | VMB | Acc.Qual. | Confirm | -0.0593 | Table 3, p. 305 |
| Barron et al. (2012) | SSRN | US | 307 | 8,606[a] | 1983-2010 | VMB | Analyst | Confirm | -0.2327 | Table 2, p. 29 |
| Barth et al. (2013) | JAE | US | 1,985 | 51,612 | 1974–2000 | RFB | Acc.Qual. | Confirm | -0.1210 | Table 1, p. 214 |
| Barth et al. (2013) | JAE | US | 1,985 | 51,612 | 1974–2000 | REAL | Acc.Qual. | Confirm | -0.0380 | Table 1, p. 214 |
| Berger, Chen, and Li (2012) | SSRN | US | 1,665 | 41,615 | 1980-2004 | RFB | Acc.Qual. | Confirm | -0.0475 | Table 7, p. 33 |
| Berger et al. (2012) | SSRN | US | 1,015 | 25,365 | 1980-2004 | VMB | Acc.Qual. | Confirm | -0.0830 | Table 5, p. 29 |
| Bhattacharya et al. (2012) | TAR | US | 1,054 | 12,648 | 1993-2005 | RFB | Acc.Qual. | Confirm | -0.1770 | In-text, p. 475 |
| Bhattacharya et al. (2012) | TAR | US | 1,054 | 12,648 | 1993-2005 | VMB | Acc.Qual. | Confirm | -0.2243 | Table 2, p. 463 |
| Botosan and Plumlee (2013) | JBFA | US | 555 | 6,656 | 1993-2004 | VMB | Analyst | Mixed | -0.1470 | Table 3, p. 1061 |
| Botosan et al. (2004) | RAST | US | 312 | 2,804 | 1993-2001 | VMB | Analyst | Mixed | -0.0930 | Table 2, p. 247 |
| Callen, Khan, and Lu (2013) | CAR | US | 1,129 | 29,345 | 1981-2006 | REAL | Acc.Qual. | Confirm | -0.0354 | Table 5 & 6, pp. 283-85 |
| Callen et al. (2013) | CAR | US | 841 | 19,336 | 1984-2006 | VMB | Acc.Qual. | Confirm | -0.0416 | Table 7, p. 287 |
| Chan, Lin, and Strong (2009) | MF | UK | 416 | 5,403 | 1987-1999 | VMB | Acc.Qual. | Mixed | -0.0190 | Table 3, p. 336 |
| Chan et al. (2009) | MF | UK | 416 | 5,403 | 1987-1999 | REAL | Acc.Qual. | Mixed | -0.0288 | Table 9, p. 342 |
| Chan, Lo, and Yang (2016) | NAJEF | US | 1,828 | 32,910 | 1996-2013 | RFB | Analyst | Confirm | -0.1203 | Table 4, p.125 |
| Chen, Dhaliwal, and Trombley (2008) | JAAF | US | 2,122 | 53,048 | 1980-2004 | REAL | Acc.Qual. | Confirm | -0.0420 | Table 2, p. 480 |
| Chen et al. (2008) | JAAF | US | 614 | 15,339 | 1980-2004 | VMB | Acc.Qual. | Confirm | -0.0433 | Table 4, p. 489 |
| Cohen (2003) | SSRN | US | 1,111 | 16,664 | 1987-2001 | VMB | Acc.Qual. | Reject | -0.0045 | Table 6 & 8, pp. 44-6 |
| Cohen (2008) | APJAE | US | 1,074 | 18,264 | 1987−2003 | VMB | Acc.Qual. | Reject | -0.0068 | Table 3, p. 83 |
| Cohen (2008) | APJAE | US | 1,074 | 18,264 | 1987−2003 | RFB | Acc.Qual. | Reject | -0.0052 | Table 4, p. 85 |
| Core et al. (2008) | JAE | US | 2,909 | 93,093 | 1970-2001 | REAL | Acc.Qual. | Reject | 0.0003 | Table 4 & 5, pp. 11-3 |
| Core et al. (2008) | JAE | US | 814 | 21,979 | 1975-2001 | VMB | Acc.Qual. | Reject | -0.0386 | Table 8, p. 18 |
| Diether et al. (2002) | JF | US | 2,908 | 66,884 | 1980-2002 | REAL | Analyst | Reject | 0.0089 | Table 9, p. 2136 |
| Diether et al. (2002) | JFQA | US | 1,203 | 22,854 | 1983-2001 | REAL | Analyst | Confirm | -0.0585 | Table 8, p. 597 |
| Eliwa, Haslam, and Abraham (2016) | IRFA | UK | 587 | 4,112 | 2005–2011 | VMB | Acc.Qual. | Confirm | -0.0714 | Table 1, p. 131 |

*Table continued next page.*

**Table 3: Information Precision on CoE – Description of Studies Included in the Meta-Analysis (cont)**

| Study | Journal* | Country† | No. of firms§ | No. of firm-years‡ | Sampling Period | DV: CoE¥ | IV: Precision£ | Direct Link? | Effect size (Pearson's *r* coefficient) | Source of Information |
|---|---|---|---|---|---|---|---|---|---|---|
| Francis et al. (2004) | TAR | US | 790 | 21,334 | 1975-2001 | VMB | Acc.Qual. | Confirm | -0.0481 | Table 5, 6 & 9, pp. 990-1001 |
| Francis, LaFond, Olsson, and Schipper (2005a) | JAE | US | 1,722 | 55,092 | 1970-2001 | VMB | Acc.Qual. | Confirm | -0.0248 | Table 2, p. 309 |
| Garcia Lara, Garcia Osma, and Penalva (2011) | RAST | US | 1,875 | 54,389 | 1975-2003 | REAL | Acc.Qual. | Confirm | -0.0139 | Table 4 & 6, pp. 261-4 |
| Gray, Koh, and Tong (2009) | JBFA | AU | 170 | 1,362 | 1998-2005 | VMB | Acc.Qual. | Confirm | -0.0676 | Table 3, p. 63 |
| Gray et al. (2009) | JBFA | AU | 170 | 1,362 | 1998-2005 | REAL | Acc.Qual. | Confirm | -0.0730 | Table 4 & 5, pp. 66-8 |
| Hou (2015) | RAST | US | 1,418 | 41,134 | 1982-2010 | VMB | Acc.Qual. | Confirm | -0.1275 | Table 2, p. 1073 |
| Hwang and Lim (2012) | APJFS | US | 645 | 9,672 | 1993-2007 | VMB | Acc.Qual. | Confirm | -0.1640 | Table 2, p. 471 |
| Kim and Qi (2010) | TAR | US | 2,802 | 103,682 | 1970-2006 | REAL | Acc.Qual. | Mixed | -0.0040 | Table 4, pp. 947-9 |
| Kim and Sohn (2013) | JAPP | US | 1,211 | 30,276 | 1987-2011 | VMB | Acc.Qual. | Confirm | -0.0673 | Table 2, p. 529 |
| Konchitchki et al. (2016) | RAST | US | 2,567 | 100,095 | 1976-2014 | REAL | Acc.Qual. | Confirm | -0.0118 | Table 5, p. 21 |
| Larson and Resutek (2015) | SSRN | US | 79 | 2,684 | 1978-2011 | REAL | Acc.Qual. | Mixed | -0.0491 | Table 6 & 8, p. 42-4 |
| Larson and Resutek (2015) | SSRN | US | 49 | 1,728 | 1977-2011 | VMB | Acc.Qual. | Mixed | -0.1102 | Table 9, p. 45 |
| Latiff and Taib (2011) | ATBMR | MY | 141 | 141 | 2004 | VMB | Acc.Qual. | Confirm | -0.1624 | Table 4, p. 6 |
| Liu and Wysocki (2016) | QJF | US | 1,454 | 68,348 | 1960-2006 | RFB | Acc.Qual. | Mixed | -0.1200 | Table 3, p. 15 |
| Liu and Wysocki (2016) | QJF | US | 945 | 44,392 | 1960-2006 | VMB | Acc.Qual. | Mixed | -0.0700 | Table 3, p. 15 |
| Mashruwala and Mashruwala (2011) | TAR | US | 2,561 | 92,187 | 1971-2006 | REAL | Acc.Qual. | Mixed | -0.0048 | Table 6, p. 1368 |
| McInnis (2010) | TAR | US | 1,777 | 56,870[b] | 1975-2006 | REAL | Acc.Qual. | Reject | -0.0025 | Table 1, p. 321 |
| McInnis (2010) | TAR | US | 438 | 14,008 | 1975-2001 | VMB | Acc.Qual. | Reject | -0.0444 | Table 4, p. 328 |
| Ogneva (2012) | TAR | US | 2,184 | 80,790 | 1970-2006 | REAL | Acc.Qual. | Mixed | -0.0048 | Table 4, pp. 1433-4 |
| Othman (2012) | AJBA | MY | 461 | 3,688 | 2000-2007 | VMB | Acc.Qual. | Confirm | -0.0319 | Table 3, p. 17 |
| Safdar and Yan (2016) | CFRI | CN | 1,251 | 8,754 | 2006-2012 | VMB | Acc.Qual. | Mixed | -0.0244 | Table 2, p. 87 |
| Safdar and Yan (2016) | CFRI | CN | 1,251 | 8,754 | 2006-2012 | REAL | Acc.Qual. | Mixed | -0.0138 | Table 3, 5, & 6, p. 89-92 |
| Sheng and Thevenot (2015) | IJF | US | 128 | 3,583[a] | 1984-2011 | VMB | Analyst | Confirm | -0.3300 | Table 2, p. 521 |

*Notes:* ** Journal names along with their ABS 2015 ranking are shown in the appendix. † AU: Australia; CN: China; MY: Malaysia; UK: United Kingdom; US: United States. § Number of firms is approximated as number of firm-years divided by number of sample years. ‡ When multiple samples are selected for one study, average sample size is reported. ¥ REAL: realised-return, RFB: risk factor-based, VMB: valuation model-based cost of equity proxy. £Acc.Qual: Accounting/Earnings Quality, Analyst: security analyst forecast based proxy. [a] Converted firm-quarters into firm-years. [b] Converted firm-months into firm-years.*

**Table 4: Information Asymmetry on CoE – Description of Studies Included in the Analysis**

| Study | Journal* | Country† | Sampling Period | DV: CoE¥ | IV: Asymmetry£ | Proxy‡ | Direct Link? | Source of Information§ |
|---|---|---|---|---|---|---|---|---|
| Akins et al. (2012) | TAR | US | 1984-2009 | REAL | Micro. | B/A | Mixed | Table 3, p. 48 |
| Akins et al. (2012) | TAR | US | 1984-2005 | REAL | Micro. | PIN | Mixed | Table 4, p. 50 |
| Amihud and Mendelson (1986) | JFE | US | 1961-1980 | REAL | Micro. | B/A | Confirm | Table 3, p. 236 |
| Armstrong et al. (2011) | JAR | US | 1988-2006 | REAL | Micro. | B/A | Mixed | Table 3 & 4, pp. 23-8 |
| Armstrong et al. (2011) | JAR | US | 1976-2006 | REAL | Non-Micro. | Acc.Qual. | Mixed | Table 3 & 4, pp. 23-8 |
| Armstrong et al. (2011) | JAR | US | 1976-2006 | REAL | Non-Micro. | Analyst | Mixed | Table 3 & 4, pp. 23-8 |
| Aslan et al. (2011) | JEF | US | 1965-2009 | REAL | Micro. | PIN | Confirm | Table 8, p. 796 |
| Barron et al. (2012) | SSRN | US | 1983-2010 | VMB | Non-Micro. | Analyst | Confirm | Table 4, p. 32-4 |
| Bhattacharya et al. (2012) | TAR | US | 1993-2005 | VMB | Micro. | B/A | Confirm | Table 2, p. 463 |
| Bhattacharya et al. (2012) | TAR | US | 1993-2005 | VMB | Micro. | PIN | Confirm | Table 2, p. 463 |
| Botosan and Plumlee (2013) | JBFA | US | 1993-2004 | VMB | Micro. | PIN | Confirm | Table 4, p. 1062 |
| Botosan and Plumlee (2013) | JBFA | US | 1993-2004 | REAL | Micro. | PIN | Reject | Table 4, p. 1062 |
| Brennan et al. (2016) | MS | US | 1983-2010 | REAL | Micro. | PIN | Confirm | Table 4 & 5, pp. 2469-70 |
| Choi, Jin, and Yan (2016) | SSRN | CN | 1996-2007 | REAL | Non-Micro. | Comp. | Confirm | Table 6, p. 36 |
| Duarte and Young (2009) | JFE | US | 1984-2004 | REAL | Micro. | PIN | Reject | Table 10, p. 136 |
| Duarte, Han, Harford, and Young (2008) | JFE | US | 1985-2000 | REAL | Micro. | PIN | Confirm | Table 5, p. 37 |
| Easley et al. (2002) | JF | US | 1984-1998 | REAL | Micro. | PIN | Confirm | Table 6, p. 2213 |
| Easley, Hvidkjaer, and O'Hara (2010) | JFQA | US | 1983-2001 | REAL | Micro. | PIN | Confirm | Table 6, p. 307 |
| Eleswarapu and Reinganum (1993) | JFE | US | 1961-1990 | REAL | Micro. | B/A | Mixed | Table 2, p. 379 |
| He, Lepone, and Leung (2013) | IREF | AU | 2001-2008 | VMB | Micro. | B/A | Confirm | Table 4 & 5, p. 617-8 |
| Hwang et al. (2013) | JAE | KR | 2000-2004 | VMB | Micro. | PIN | Mixed | Table 5, p. 158 |
| Hwang et al. (2013) | JAE | KR | 1995-2005 | REAL | Micro. | PIN | Mixed | Table 9, p. 162 |
| Kang (2010) | JBF | US | 1984-2002 | REAL | Micro. | PIN | Mixed | Table 4, p. 2990 |
| Levi and Zhang (2015) | MS | US | 1993-2003 | REAL | Micro. | B/A | Confirm | Table 3, p. 361 |

*Table continued next page.*

**Table 4: Information Asymmetry on CoE – Description of Studies Included in the Analysis (cont.)**

| Study | Journal* | Country† | Sampling Period | DV: CoE¥ | IV: Asymmetry£ | Proxy‡ | Direct Link? | Source of Information§ |
|---|---|---|---|---|---|---|---|---|
| Luong et al. (2011) | SSRN | US | 1984-2006 | REAL | Micro. | PIN | Mixed | Table 5, pp. 46-7 |
| Mohanram and Rajgopal (2009) | JAE | US | 1984-2002 | VMB | Micro. | PIN | Reject | Table 7, p. 239 |
| Mohanram and Rajgopal (2009) | JAE | US | 1984-2002 | REAL | Micro. | PIN | Reject | Table 1, p. 230 |
| Yan and Zhang (2014) | JBF | US | 1983-2005 | REAL | Micro. | PIN | Confirm | Table 8, p. 147 |

*Notes:* ** Journal names along with their ABS 2015 ranking are shown in the appendix. † AU: Australia; CN: China; KR: South Korea; US: United States. ¥ REAL: realised-return, VMB: valuation model-based cost of equity proxy. £(Non-)Micro.: (Non-)Microstructure-based proxies. ‡ B/A: Bid/Ask-spreads; PIN: Probability of informed trading scores; Acc.Qual.: Accounting/Earnings Quality, Comp.: market competition, Analyst: security analyst forecast based proxy. § Information used to decide if a study confirms/rejects or finds mixed results regarding the direct link between Asymmetry and CoE.*

**Table 5: Descriptive Statistics of Quantity, Precision and Asymmetry Studies**

| | Quantity | | Precision | | Asymmetry | | Total | |
|---|---|---|---|---|---|---|---|---|
| **Sample** | | | | | | | | |
| Observations | 62 | 100% | 48 | 100% | 28 | 100% | 138 | 100% |
| Studies | 56 | 90% | 35 | 73% | 22 | 79% | 113 | 82% |
| **Direct Link** | | | | | | | | |
| Accept | 44 | 71% | 27 | 56% | 16 | 57% | 87 | 63% |
| Reject | 6 | 10% | 8 | 17% | 4 | 14% | 18 | 13% |
| Mixed | 12 | 19% | 13 | 27% | 8 | 29% | 33 | 24% |
| **Published Work** | | | | | | | | |
| Yes | 50 | 81% | 42 | 88% | 25 | 89% | 117 | 85% |
| No | 12 | 19% | 6 | 13% | 3 | 11% | 21 | 15% |
| **Publ. Quality** | | | | | | | | |
| Higher-Tier | 37 | 60% | 29 | 60% | 24 | 86% | 90 | 65% |
| Lower-Tier | 25 | 40% | 19 | 40% | 4 | 14% | 48 | 35% |
| **Country** | | | | | | | | |
| US | 25 | 40% | 41 | 85% | 24 | 86% | 90 | 65% |
| Non-US | 37 | 60% | 7 | 15% | 4 | 14% | 48 | 35% |
| **CoE Proxy** | | | | | | | | |
| REAL | 6 | 10% | 16 | 33% | 21 | 75% | 43 | 31% |
| VMB | 50 | 81% | 26 | 54% | 7 | 25% | 83 | 60% |
| RFB | 6 | 10% | 6 | 13% | 0 | 0% | 12 | 9% |
| **Quantity Proxy** | | | | | | | | |
| Disclosure | 62 | 100% | | | | | 62 | 45% |
| thereof: FF/PF/NF | 11/29/22 | 18/47/35% | | | | | 62 | 45% |
| thereof: SCI/EXI/Dummy | 38/13/11 | 61/21/18% | | | | | 62 | 45% |
| **Precision Proxy** | | | | | | | | |
| Acc. Quality | | | 41 | 85% | | | 41 | 30% |
| Analyst | | | 7 | 15% | | | 7 | 5% |
| **Asymmetry Proxy** | | | | | | | | |
| Micro. | | | | | 24 | 86% | 24 | 17% |
| Non-Micro. | | | | | 4 | 14% | 4 | 3% |

*Notes: This table reports descriptive statistics of the Quantity, Precision and Asymmetry studies included in the literature review for several sample characteristics: (i) Sample: number of studies and observations included; (ii) Direct Link: number of observations (no. of obs.) accepting, rejecting, and finding mixed results for the link with CoE; (iii) Published Work: no. of obs. which are published and unpublished; (iv): Publication Quality: no. of obs. appearing in higher-tier journals (4 & 3 rated journals in ABS 2015 list) and lower-tier journals (ABS 2015 2 & 1 rated, unranked and unpublished work); (v) Country: no. of obs. focusing on US and non-US firms; (vi) CoE Proxy: no. of obs. using realised-return (REAL), risk factor-based (RFB) and valuation model-based (VMB) cost of equity proxies; (vii): Quantity Proxy: no. of obs. focusing on full-financial (FF), part-financial (PF), non-financial (NF) disclosure and using self-constructed indices (SCI), external third-party indices (EXI) and binary dummy variables (Dummy) to measures quantity; (viii) Precision Proxy: no. of obs. applying accounting quality (Acc. Quality) and analyst-based (Analyst) proxies; (ix) Asymmetry Proxy: no. of obs. using microstructure (Micro.) and non- microstructure-based proxies;*

**Table 6: Results by Disclosure Types and CoE Measures**

| | **Full-Financial (FF)** | **Partial-Financial (PF)** | **Non-Financial (NF)** | Total |
|---|---|---|---|---|
| **RFB/VMB** | | | | |
| r: | -0.117** | -0.069 | -0.053 | -0.075 |
| 95% CI: | [-0.215; -0.018] | [-0.215; 0.078] | [-0.167; 0.060] | [-0.204; 0.054] |
| $\frac{S_e^2}{S_r^2}$: | 0.288 | 0.331 | 0.263 | 0.258 |
| $\chi^2_{K-1}$: | 38.14*** | 72.55*** | 79.85*** | 217.38*** |
| K: | 11 | 24 | 21 | 56 |
| Sample: | 10,423 | 8,625 | 17,560 | 36,607 |
| **REAL** | | | | |
| r: | - | -0.025 | -0.060 | -0.026 |
| 95% CI: | - | [-0.066; 0.017] | [-0.060; -0.060]# | [-0.063; 0.011] |
| $\frac{S_e^2}{S_r^2}$: | - | 0.599 | - | 0.686 |
| $\chi^2_{K-1}$: | - | 8.34 | - | 8.75 |
| K: | - | 5 | 1 | 6 |
| Sample: | - | 7,460 | 333 | 7,793 |
| Total | | | | |
| r: | -0.117** | -0.048 | -0.054 | -0.066 |
| 95% CI: | [-0.215; -0.018] | [-0.167; 0.071] | [-0.165; 0.058] | [-0.190; 0.058] |
| $\frac{S_e^2}{S_r^2}$: | 0.288 | 0.328 | 0.275 | 0.257 |
| $\chi^2_{K-1}$: | 38.14*** | 88.42*** | 79.86*** | 241.21*** |
| K: | 11 | 29 | 22 | 62 |
| Sample: | 10,423 | 16,085 | 17,892 | 44,400 |

*Notes: This contingency table reports average effect size (r), the 95 percent confidence interval (95% CI), the sampling-error explained percentage of observed variance ($S_e^2/S_r^2$), the chi-square statistic ($\chi^2_{K-1}$), number of studies (K) and sample size as the average number of firms per year (sample) for the association between information quantity and CoE. RFB/VMB contains studies using risk factor-based and/or valuation model-based CoE measures; REAL subsumes studies using realised returns as CoE proxy. Distinction is made between studies focusing fully (FF), partially (PF) or not at all (NF) on financial disclosure. # zero residual variance is used for CI calculation, given the error variance ($Se^2$) being larger than the observed variance ($Sr^2$) resulting in a negative population variance ($Sp^2$). ***, **, * denotes significance at the 0.01, 0.05, 0.10 level.*

**Table 7: Results by Disclosure Types and Disclosure Metrics**

| | **Full-Financial (FF)** | **Partial-Financial (PF)** | **Non-Financial (NF)** | Total |
|---|---|---|---|---|
| **SCI** | | | | |
| r: | -0.101*** | -0.039 | -0.052 | -0.050 |
| 95% CI: | [-0.215; -0.018] | [-0.145; 0.067] | [-0.217; 0.12] | [-0.179; 0.079] |
| $\frac{S_e^2}{S_r^2}$: | 0.654 | 0.317 | 0.205 | 0.270 |
| $\chi^2_{K-1}$: | 9.17* | 60.00*** | 63.36*** | 140.89*** |
| K: | 6 | 19 | 13 | 38 |
| Sample: | 2,537 | 13,934 | 7,098 | 23,569 |
| **EXI** | | | | |
| r: | -0.049 | -0.128* | -0.026 | -0.104 |
| 95% CI: | [-0.049; -0.049]# | [-0.278; 0.022] | [-0.026; -0.026]# | [-0.231; 0.023] |
| $\frac{S_e^2}{S_r^2}$: | 1509.313 | 0.500 | 1.980 | 0.594 |
| $\chi^2_{K-1}$: | 0.00 | 18.00** | 1.01 | 21.89** |
| K: | 2 | 9 | 2 | 13 |
| Sample: | 456 | 1,492 | 127 | 2,075 |
| **Dummy** | | | | |
| r: | -0.126** | -0.062 | -0.055* | -0.083 |
| 95% CI: | [-0.232; -0.020] | [-0.062; -0.062]# | [-0.109; 0.00] | [-0.186; 0.020] |
| $\frac{S_e^2}{S_r^2}$: | 0.117 | - | 0.456 | 0.173 |
| $\chi^2_{K-1}$: | 25.60*** | - | 15.36** | 63.47*** |
| K: | 3 | 1 | 7 | 11 |
| Sample: | 7,430 | 659 | 10,667 | 18,756 |
| Total | | | | |
| r: | -0.117** | -0.048 | -0.054 | -0.066 |
| 95% CI: | [-0.215; -0.018] | [-0.167; 0.071] | [-0.165; 0.058] | [-0.190; 0.058] |
| $\frac{S_e^2}{S_r^2}$: | 0.288 | 0.328 | 0.275 | 0.257 |
| $\chi^2_{K-1}$: | 38.14*** | 88.42*** | 79.86*** | 241.21*** |
| K: | 11 | 29 | 22 | 62 |
| Sample: | 10,423 | 16,085 | 17,892 | 44,400 |

*Notes: This contingency table reports average effect size (r), the 95 percent confidence interval (95% CI), the sampling-error explained percentage of observed variance ($S_e^2/S_r^2$), the chi-square statistic ($\chi^2_{K-1}$), number of studies (K) and sample size as the average number of firms per year (sample) for the association between information quantity and CoE. Distinction is made between type of disclosures—studies focusing fully (FF), partially (PF) or not at all (NF) on financial disclosure—and disclosure metrics— studies using self-constructed disclosure indexes (SCI), externally provided third-party indices (EXI) or simple dummy variables to distinguish between disclosing and non-disclosing firms (Dummy). # zero residual variance is used for CI calculation, given the error variance ($Se^2$) being larger than the observed variance ($Sr^2$) resulting in a negative population variance ($Sp^2$). ***, **, * denotes significance at the 0.01, 0.05, 0.10 level.*

**Table 8: Results by Disclosure Types and Disclosure Regimes**

| | Full-Financial (FF) | Partial-Financial (PF) | Non-Financial (NF) | Total |
|---|---|---|---|---|
| *Panel A: US and Non-US Firms* | | | | |
| **US** | | | | |
| r: | -0.050 | -0.056** | -0.022 | -0.039 |
| 95% CI: | [-0.136; 0.035] | [-0.102; -0.010] | [-0.073; 0.028] | [-0.104; 0.026] |
| $\frac{S_e^2}{S_r^2}$: | 0.484 | 0.720 | 0.592 | 0.539 |
| $\chi^2_{K-1}$: | 12.39* | 13.88 | 15.20* | 46.38*** |
| K: | 6 | 10 | 9 | 25 |
| Sample: | 3,346 | 6,986 | 9,267 | 19,599 |
| **Non-US** | | | | |
| r: | -0.131 | -0.173* | -0.098 | -0.139 |
| 95% CI: | [-0.131; -0.131]# | [-0.375; 0.028] | [-0.264; 0.069] | [-0.361; 0.037] |
| $\frac{S_e^2}{S_r^2}$: | 1.352 | 0.437 | 0.517 | 0.478 |
| $\chi^2_{K-1}$: | 2.96 | 34.33*** | 19.33** | 60.68*** |
| K: | 4 | 15 | 10 | 29 |
| Sample: | 768 | 1,720 | 1,266 | 3,754 |
| *Panel B: High and Low Disclosure Regulation* | | | | |
| **HIGH** | | | | |
| r: | -0.117** | -0.035 | -0.053 | -0.062 |
| 95% CI: | [-0.220; -0.014] | [-0.093; 0.024] | [-0.166; 0.061] | [-0.176; 0.052] |
| $\frac{S_e^2}{S_r^2}$: | 0.262 | 0.544 | 0.203 | 0.221 |
| $\chi^2_{K-1}$: | 38.13*** | 27.58** | 69.05*** | 176.65*** |
| K: | 10 | 15 | 14 | 39 |
| Sample: | 9,978 | 14,118 | 16,351 | 40,446 |
| **LOW** | | | | |
| r: | -0.111 | -0.153 | -0.083 | -0.126 |
| 95% CI: | [-0.111; -0.111]# | [-0.381; 0.075] | [-0.187; 0.021] | [-0.314; 0.061] |
| $\frac{S_e^2}{S_r^2}$: | - | 0.320 | 0.721 | 0.400 |
| $\chi^2_{K-1}$: | - | 37.47*** | 9.71 | 50.04*** |
| K: | 1 | 12 | 7 | 20 |
| Sample: | 445 | 1,800 | 944 | 3,188 |

*Table continued next page.*

## Table 8: Results by Disclosure Types and Disclosure Regimes (cont.)

| *Panel C: High (HDE) and Low Disclosure Environments (LDE)* | | | | |
|---|---|---|---|---|
| | **Full-Financial (FF)** | **Partial-Financial (PF)** | **Non-Financial (NF)** | Total |
| **HDE** | | | | |
| r: | -0.060 | -0.056*** | -0.026 | -0.043 |
| 95% CI: | [-0.159; 0.039] | [-0.097; -0.015] | [-0.107; 0.054] | [-0.122; 0.037] |
| $\frac{S_e^2}{S_r^2}$: | 0.490 | 0.782 | 0.426 | 0.489 |
| $\chi^2_{K-1}$: | 18.38** | 14.07 | 28.14*** | 65.46*** |
| K: | 9 | 11 | 12 | 32 |
| Sample: | 3,668 | 7,016 | 9,590 | 20,275 |
| **LDE** | | | | |
| r: | -0.111 | -0.186* | -0.083 | -0.141 |
| 95% CI: | [-0.111; -0.111]# | [-0.398; 0.026] | [-0.187; 0.021] | [-0.326; 0.044] |
| $\frac{S_e^2}{S_r^2}$: | - | 0.390 | 0.721 | 0.429 |
| $\chi^2_{K-1}$: | - | 30.74*** | 9.71 | 46.66*** |
| K: | 1 | 12 | 7 | 20 |
| Sample: | 445 | 1,491 | 944 | 2,879 |
| Total | | | | |
| r: | -0.117** | -0.048 | -0.054 | -0.066 |
| 95% CI: | [-0.215; -0.018] | [-0.167; 0.071] | [-0.165; 0.058] | [-0.190; 0.058] |
| $\frac{S_e^2}{S_r^2}$: | 0.288 | 0.328 | 0.275 | 0.257 |
| $\chi^2_{K-1}$: | 38.14*** | 88.42*** | 79.86*** | 241.21*** |
| K: | 11 | 29 | 22 | 62 |
| Sample: | 10,423 | 16,085 | 17,892 | 44,400 |

*Notes: This contingency table reports average effect size (r), the 95 percent confidence interval (95% CI), the sampling-error explained percentage of observed variance ($S_e^2/S_r^2$), the chi-square statistic ($\chi^2_{K-1}$), number of studies (K) and sample size as the average number of firms per year (sample) for the association between information quantity and CoE. Distinction is made between types of disclosures (i.e., studies focusing fully (FF), partially (PF) or not at all (NF) on financial disclosure) and the following disclosure regimes: Panel A reports results for US and non-US firms, Panel B categorises studies according to their disclosure regulation scores, with studies below the sample average of 0.83 being assigned to the LOW group and the remainder to the HIGH group; Panel C distinguishes between high disclosure environments (HDE: US, CA, UK) and a low disclosure environments (LDE: AUS, BR, CH, DE, EG, FR, ID, MY, SP, TW) with the respective countries assigned to each group in parentheses. # zero residual variance is used for CI calculation, given the error variance ($Se^2$) being larger than the observed variance ($Sr^2$) resulting in a negative population variance ($Sp^2$). ***, **, * denotes significance at the 0.01, 0.05, 0.10 level.*

## Table 9: Results by Information Precision and CoE Measures

| | **Acc.Qual.** | **Analyst** | Total |
|---|---|---|---|
| **RFB/VMB** | | | |
| r: | -0.074 | -0.142*** | -0.082 |
| 95% CI: | [-0.168; 0.020] | [-0.211; -0.073] | [-0.183; 0.019] |
| $\frac{S_e^2}{S_r^2}$: | 0.324 | 0.554 | 0.304 |
| $\chi^2_{K-1}$: | 83.21*** | 9.03* | 105.13*** |
| K: | 27 | 5 | 32 |
| Sample: | 24,194 | 3,130 | 27,324 |
| **REAL** | | | |
| r: | -0.014 | -0.011 | -0.014 |
| 95% CI: | [-0.014; -0.014]# | [-0.053; 0.031] | [-0.014; -0.014]# |
| $\frac{S_e^2}{S_r^2}$: | 2.484 | 0.517 | 1.675 |
| $\chi^2_{K-1}$: | 5.63 | 3.87 | 9.55 |
| K: | 14 | 2 | 16 |
| Sample: | 23,826 | 4,111 | 27,937 |
| Total | | | |
| r: | -0.044 | -0.067 | -0.048 |
| 95% CI: | [-0.129; 0.040] | [-0.206; 0.071] | [-0.142; 0.047] |
| $\frac{S_e^2}{S_r^2}$: | 0.313 | 0.161 | 0.270 |
| $\chi^2_{K-1}$: | 131.18*** | 43.50*** | 177.89*** |
| K: | 41 | 7 | 48 |
| Sample: | 48,020 | 7,241 | 55,261 |

*Notes: This contingency table reports average effect size (r), the 95 percent confidence interval (95% CI), the sampling-error explained percentage of observed variance ($S_e^2/S_r^2$), the chi-square statistic ($\chi^2_{K-1}$), number of studies (K) and sample size as the average number of firms per year (sample) for the association between Information Precision and CoE. RFB/VMB contains studies using risk factor-based and/or valuation model-based CoE measures; REAL subsumes studies using realised returns as CoE proxy. Distinction is made between studies applying accounting quality (Acc.Qual.) and analyst-based (Analyst) proxies for Precision. # zero residual variance is used for CI calculation, given the error variance ($Se^2$) being larger than the observed variance ($Sr^2$) resulting in a negative population variance ($Sp^2$). ***, **, * denotes significance at the 0.01, 0.05, 0.10 level.*

**Table 10: Results by Accounting Quality and CoE Measures**

| | **AQ-Metric** | **Non-AQ-Metric** | Total |
|---|---|---|---|
| **RFB/VMB** | | | |
| r: | -0.082 | -0.063*** | -0.074 |
| 95% CI: | [-0.203; 0.038] | [-0.083; -0.043] | [-0.168; 0.020] |
| $\frac{S_e^2}{S_r^2}$: | 0.220 | 0.918 | 0.324 |
| $\chi^2_{K-1}$: | 68.04*** | 13.08 | 83.21*** |
| K: | 15 | 12 | 27 |
| Sample: | 13,891 | 10,303 | 24,194 |
| **REAL** | | | |
| r: | -0.011 | -0.020 | -0.014 |
| 95% CI: | [-0.011; -0.011]# | [-0.020; -0.020]# | [-0.014; -0.014]# |
| $\frac{S_e^2}{S_r^2}$: | 2.060 | 3.889 | 1.675 |
| $\chi^2_{K-1}$: | 3.40 | 1.80 | 5.63 |
| K: | 7 | 7 | 14 |
| Sample: | 13,998 | 9,827 | 23,826 |
| Total | | | |
| r: | -0.046 | -0.042** | -0.044 |
| 95% CI: | [-0.154; 0.061] | [-0.074; -0.010] | [-0.129; 0.040] |
| $\frac{S_e^2}{S_r^2}$: | 0.206 | 0.780 | 0.313 |
| $\chi^2_{K-1}$: | 106.59*** | 24.37 | 131.18*** |
| K: | 22 | 19 | 41 |
| Sample: | 27,889 | 20,131 | 48,020 |

*Notes: This contingency table reports average effect size (r), the 95 percent confidence interval (95% CI), the sampling-error explained percentage of observed variance ($S_e^2/S_r^2$), the chi-square statistic ($\chi^2_{K-1}$), number of studies (K) and sample size as the average number of firms per year (sample) for the association between Accounting Quality and CoE. RFB/VMB contains studies using risk factor-based and/or valuation model-based CoE measures; REAL subsumes studies using realised returns as CoE proxy. Distinction is made between studies applying an accrual quality metric (AQ-Metric) and those alternative accounting quality measures (Non-AQ-Metric). # zero residual variance is used for CI calculation, given the error variance ($Se^2$) being larger than the observed variance ($Sr^2$) resulting in a negative population variance ($Sp^2$). ***, **, * denotes significance at the 0.01, 0.05, 0.10 level.*

## Table 11: Results by Disclosure Types, CoE Measures and Publication Quality

| | **Full-Financial (FF)** | | **Partial-Financial (PF)** | | **Non-Financial (NF)** | | Total | |
|---|---|---|---|---|---|---|---|---|
| **RFB/VMB** | Higher-Tier | Lower-Tier | Higher-Tier | Lower-Tier | Higher-Tier | Lower-Tier | Higher-Tier | Lower-Tier |
| r: | -0.119** | -0.044 | -0.057 | -0.133 | -0.061 | -0.040 | -0.081 | -0.055 |
| 95% CI: | [-0.219; -0.020] | [-0.044; -0.044] | [-0.172; 0.058] | [-0.352; 0.085] | [-0.187; 0.064] | [-0.121; 0.041] | [-0.208; 0.047] | [-0.184; 0.073] |
| $\frac{S_e^2}{S_r^2}$: | 0.252 | 9.654 | 0.322 | 0.410 | 0.194 | 0.469 | 0.209 | 0.401 |
| $\chi^2_{K-1}$: | 35.8*** | 0.2 | 37.3*** | 29.3*** | 56.7*** | 21.3** | 153.3*** | 59.8*** |
| K: | 9 | 2 | 12 | 12 | 11 | 10 | 32 | 24 |
| Sample: | 10,033 | 390 | 7,286 | 1,340 | 11,007 | 6,553 | 28,325 | 8,282 |
| **REAL** | Higher-Tier | Lower-Tier | Higher-Tier | Lower-Tier | Higher-Tier | Lower-Tier | Higher-Tier | Lower-Tier |
| r: | - | - | -0.018 | -0.158 | -0.060 | - | -0.020 | -0.158 |
| 95% CI: | - | - | [-0.018; -0.018]# | [-0.158; -0.158]# | [-0.060; -0.060]# | - | [-0.020; -0.020]# | [-0.158; -0.158]# |
| $\frac{S_e^2}{S_r^2}$: | - | - | 2.534 | - | - | - | 2.329 | - |
| $\chi^2_{K-1}$: | - | - | 1.6 | - | - | - | 2.2 | - |
| K: | - | - | 4 | 1 | 1 | - | 5 | 1 |
| Sample: | - | - | 7,099 | 361 | 333 | - | 7,432 | 361 |
| Total | Higher-Tier | Lower-Tier | Higher-Tier | Lower-Tier | Higher-Tier | Lower-Tier | Higher-Tier | Lower-Tier |
| r: | -0.119** | -0.044 | -0.038 | -0.138 | -0.061 | -0.040 | -0.068 | -0.059 |
| 95% CI: | [-0.219; -0.020] | [-0.044; -0.044]# | [-0.124; 0.049] | [-0.328; 0.051] | [-0.184; 0.061] | [-0.121; 0.041] | [-0.170; 0.034] | [-0.190; 0.071] |
| $\frac{S_e^2}{S_r^2}$: | 0.252 | 9.654 | 0.362 | 0.440 | 0.212 | 0.469 | 0.209 | 0.393 |
| $\chi^2_{K-1}$: | 35.8*** | 0.2 | 44.2*** | 29.6*** | 56.7*** | 21.3** | 177.1*** | 63.6*** |
| K: | 9 | 2 | 16 | 13 | 12 | 10 | 37 | 25 |
| Sample: | 10,033 | 390 | 14,385 | 1,701 | 11,340 | 6,553 | 35,757 | 8,643 |

*Notes: This contingency table reports average effect size (r), the 95 percent confidence interval (95% CI), the sampling-error explained percentage of observed variance ($S_e^2/S_r^2$), the chi-square statistic ($\chi^2_{K-1}$), number of studies (K) and sample size as the average number of firms per year (sample) for the association between information quantity and CoE. RFB/VMB contains studies using risk factor-based and/or valuation model-based CoE measures; REAL subsumes studies using realised returns as CoE proxy. Distinction is made between studies focusing fully (FF), partially (PF) or not at all (NF) on financial disclosure. Higher-Tier: 4 & 3 rated journals in ABS2015; Lower-Tier: 2 & 1 rated journals in ABS 2015, unranked and unpublished work. # zero residual variance is used for CI calculation, given the error variance (Se²) being larger than the observed variance (Sr²) resulting in a negative population variance (Sp²). ***, **, * denotes significance at the 0.01, 0.05, 0.10 level.*

**Table 12: Results by Accounting Quality, CoE Measures and Publication Quality**

| | **Acc.Qual.** | | **Analyst** | | Total | |
|---|---|---|---|---|---|---|
| **RFB/VMB** | Higher-Tier | Lower-Tier | Higher-Tier | Lower-Tier | Higher-Tier | Lower-Tier |
| r: | -0.092* | -0.054 | -0.154*** | -0.136*** | -0.097* | -0.067 |
| 95% CI: | [-0.194; 0.009] | [-0.119; 0.011] | [-0.248; -0.060] | [-0.187; -0.086] | [-0.202; 0.009] | [-0.153; 0.019] |
| $\frac{S_e^2}{S_r^2}$: | 0.273 | 0.523 | 0.555 | 0.580 | 0.283 | 0.376 |
| $\chi^2_{K-1}$: | 47.6*** | 26.8** | 5.4* | 3.4* | 56.5*** | 42.6*** |
| K: | 13 | 14 | 3 | 2 | 16 | 16 |
| Sample: | 12,698 | 11,496 | 994 | 2,136 | 13,692 | 13,632 |
| **REAL** | Higher-Tier | Lower-Tier | Higher-Tier | Lower-Tier | Higher-Tier | Lower-Tier |
| r: | -0.014 | -0.019 | -0.011 | - | -0.014 | -0.019 |
| 95% CI: | [-0.014; -0.014]# | [-0.019; -0.019# | [-0.053; 0.031] | - | [-0.014; -0.014]# | [-0.019; -0.019# |
| $\frac{S_e^2}{S_r^2}$: | 2.019 | 20.503 | 0.517 | - | 1.389 | 20.503 |
| $\chi^2_{K-1}$: | 5.4 | 0.1 | 3.9 | - | 9.4 | 0.1 |
| K: | 11 | 3 | 2 | - | 13 | 3 |
| Sample: | 22,081 | 1,745 | 4,111 | - | 26,192 | 1,745 |
| Total | Higher-Tier | Lower-Tier | Higher-Tier | Lower-Tier | Higher-Tier | Lower-Tier |
| r: | -0.043 | -0.049* | -0.039 | -0.136*** | -0.042 | -0.061 |
| 95% CI: | [-0.135; 0.050] | [-0.108; 0.009] | [-0.162; 0.085] | [-0.187; 0.086] | [-0.139; 0.055] | [-0.144; 0.021] |
| $\frac{S_e^2}{S_r^2}$: | 0.235 | 0.591 | 0.197 | 0.580 | 0.283 | 0.411 |
| $\chi^2_{K-1}$: | 102.0*** | 28.8** | 25.4*** | 3.4* | 127.5*** | 46.3*** |
| K: | 24 | 17 | 5 | 2 | 29 | 19 |
| Sample: | 34,779 | 13,241 | 5,105 | 2,136 | 39,884 | 15,377 |

*Notes: This contingency table reports average effect size (r), the 95 percent confidence interval (95% CI), the sampling-error explained percentage of observed variance ($S_e^2/S_r^2$), the chi-square statistic ($\chi^2_{K-1}$), number of studies (K) and sample size as the average number of firms per year (sample) for the association between Information Precision and CoE. RFB/VMB contains studies using risk factor-based and/or valuation model-based CoE measures; REAL subsumes studies using realised returns as CoE proxy. Distinction is made between studies applying accounting quality (Acc.Qual.) and analyst-based (Analyst) proxies for Precision. Higher-Tier: 4 & 3 rated journals in ABS2015; Lower-Tier: 2 & 1 rated journals in ABS 2015, unranked and unpublished work. # zero residual variance is used for CI calculation, given the error variance ($Se^2$) being larger than the observed variance ($Sr^2$) resulting in a negative population variance ($Sp^2$). ***, **, * denotes significance at the 0.01, 0.05, 0.10 level.*

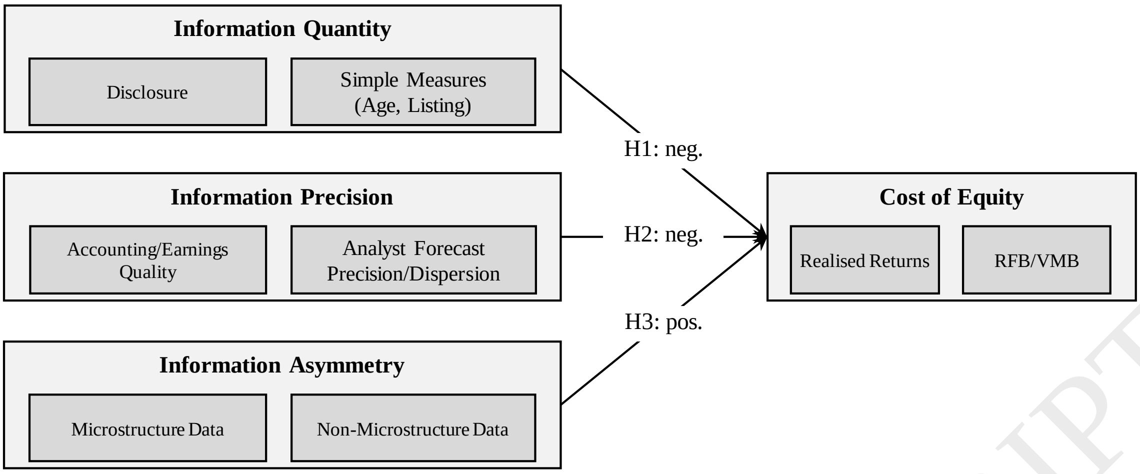



**Figure 1: Conceptual Framework**

*This figure illustrates the direct links between the information attributes and CoE. For each attribute, the most commonly used empirical measures are indicated. VMB (RFB) Valuation model-based (Risk factor-based) cost of equity proxies.*

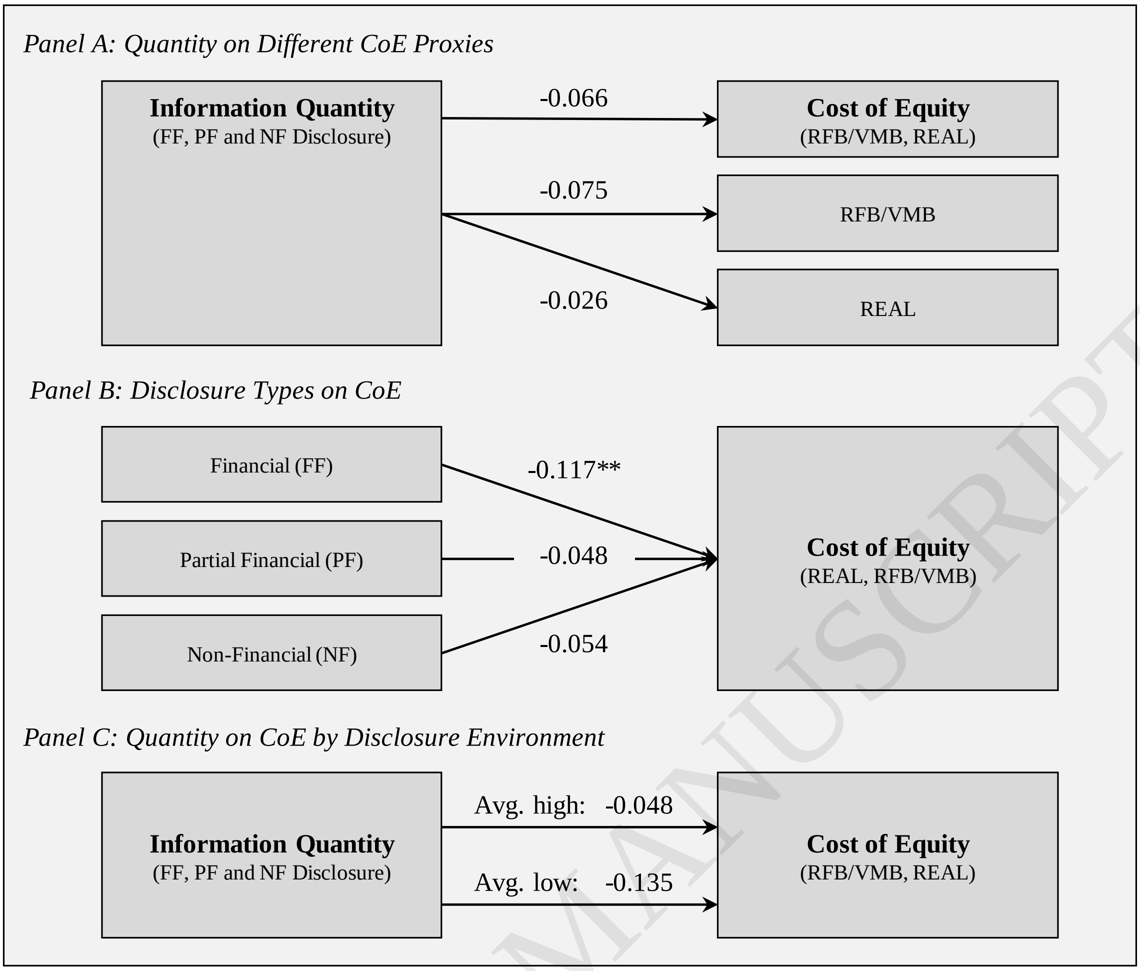



**Figure 2: Information Quantity on CoE – Main Findings**

*This figure summarises key findings from the meta-analysis of information quantity with CoE. Panel A shows average effect sizes for different measures of CoE, while Panel B distinguishes between disclosure types. Panel C reports average effect sizes between Quantity and CoE where average high (low) equals the mean effect size of US, HIGH, HDE (Non-US, LOW, LDE) as defined in Table 8. ***, **, * denotes significance at the 0.01, 0.05, 0.10 level.*

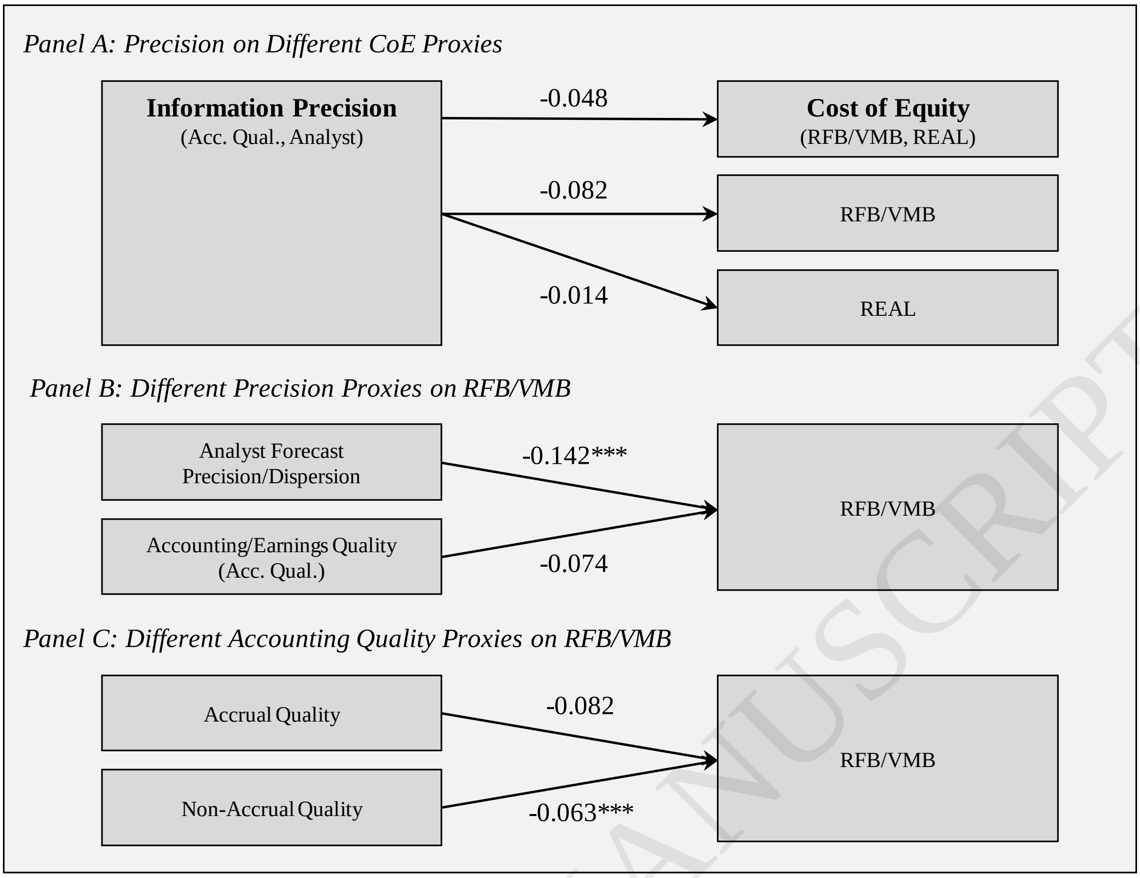



**Figure 3: Information Precision on CoE – Main Findings**

*This figure summarises key findings from the meta-analysis of information precision with CoE. Panel A shows average effect sizes for different measures of CoE. Panel B (Panel C) reports average effect sizes between different proxies for Precision (Accounting Quality) and RFB/VMB CoE proxies. ***, **, * denotes significance at the 0.01, 0.05, 0.10 level.*

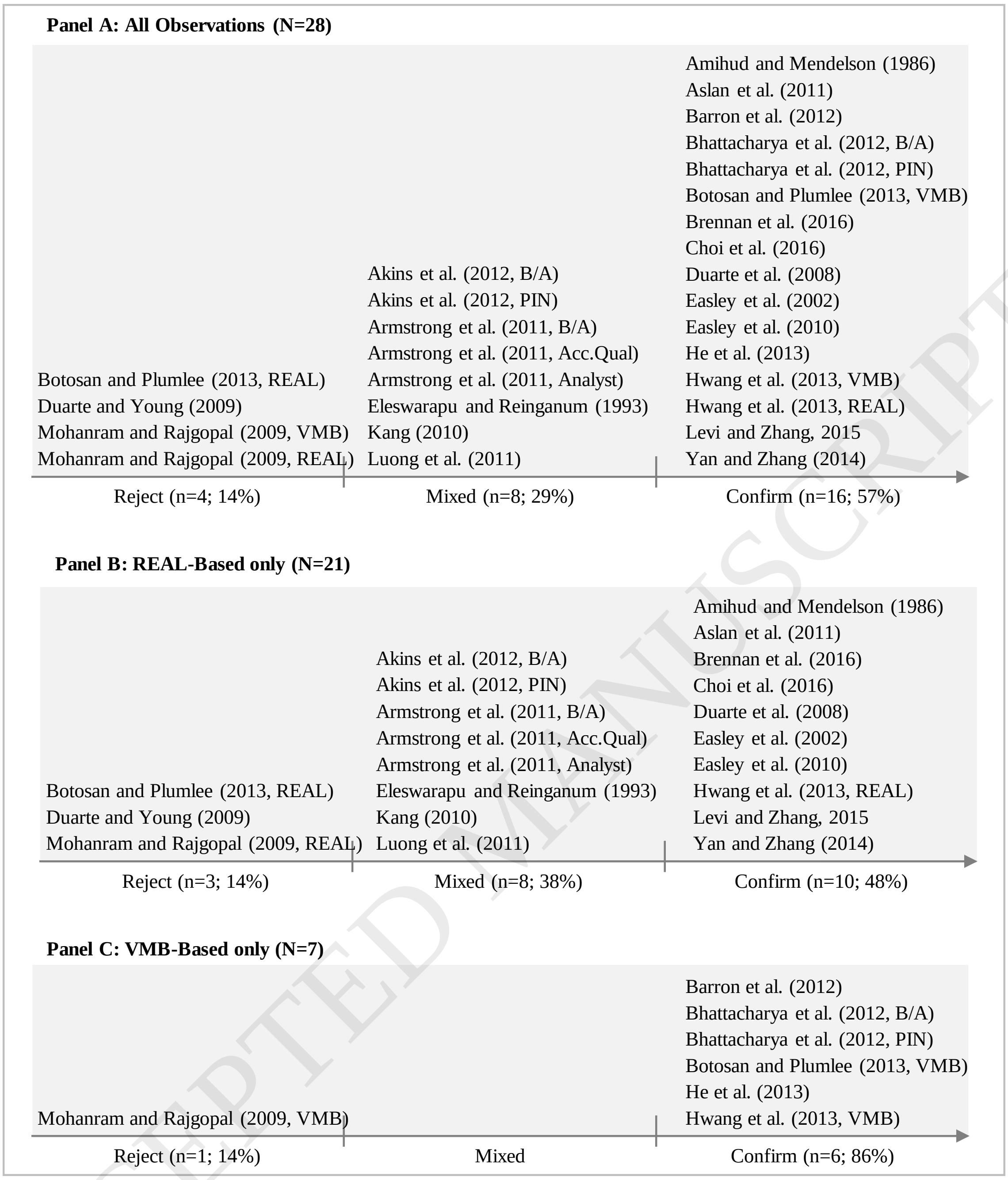
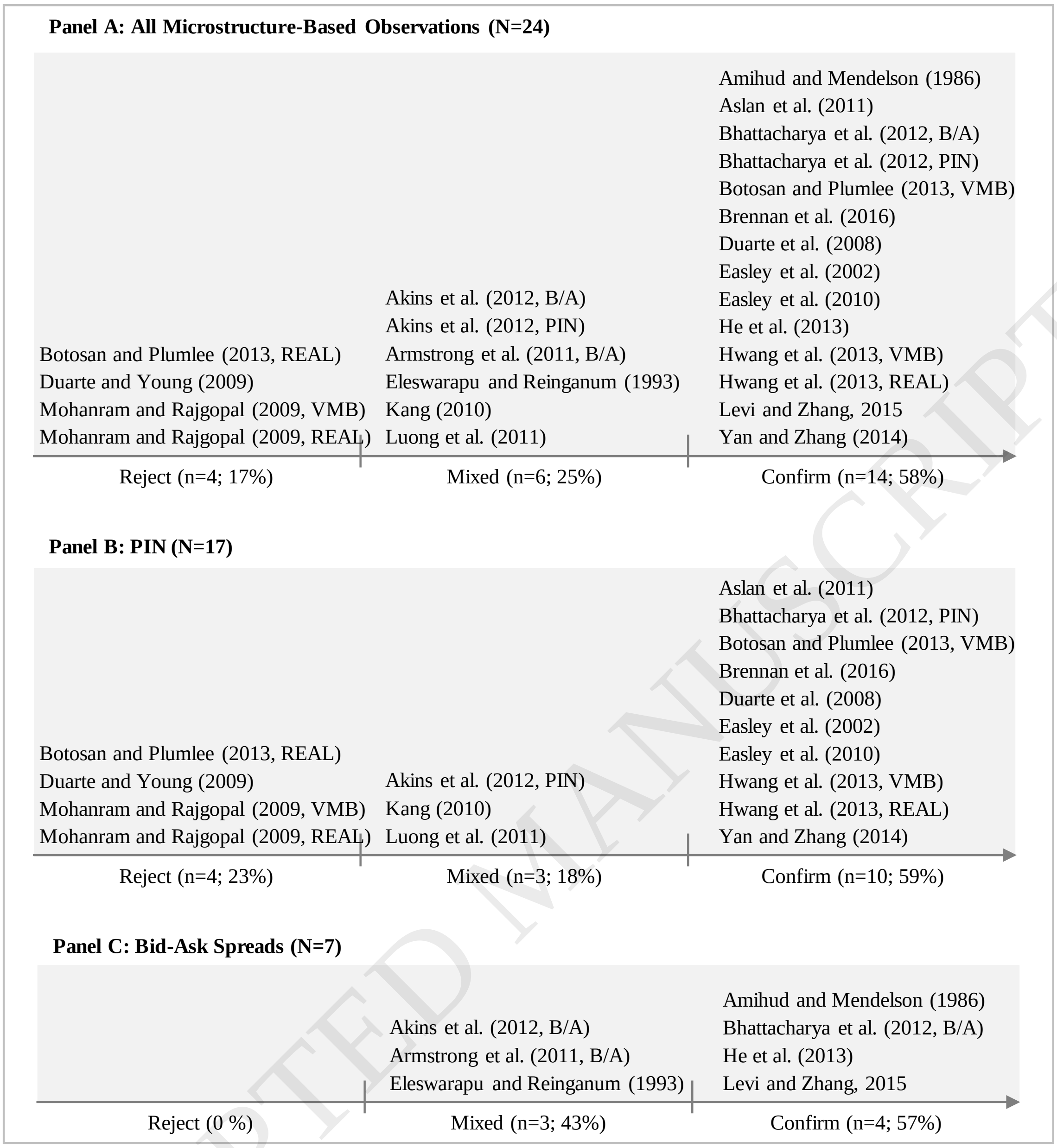



**Figure 4: Information Asymmetry on CoE – Measurement of Cost of Equity**

*The figure categorises the sample observations in respect to their general conclusion reached regarding Hypothesis 2. Panel A shows results for all observations. Panel B and Panel C for REAL-based and VMB-Based observations, respectively.*




## Figure 5: Information Asymmetry on CoE – Measurement of Information Asymmetry

*The figure categorises the sample observations in respect to their general conclusion reached regarding Hypothesis 2: The higher (lower) the information asymmetry between investors, the higher (lower) the firm's CoE. Panel A shows results for all microstructure-based observations. Panel B and Panel C for PIN-based and Bid/Ask-Spread-Based observations, respectively.*

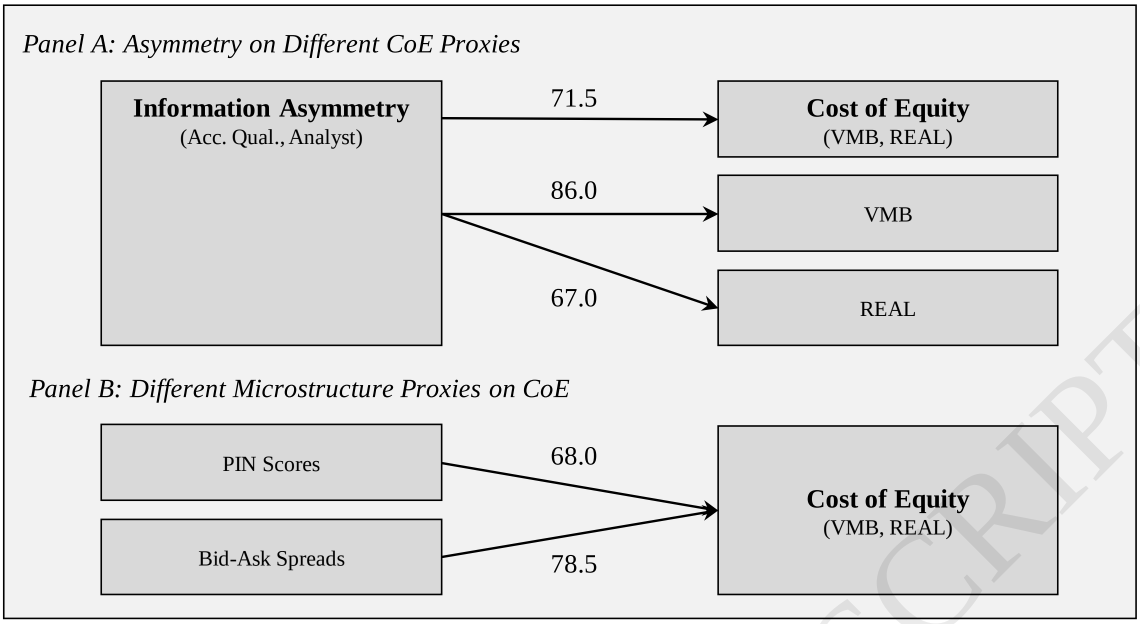



**Figure 6: Information Asymmetry on CoE – Main Findings**

*This figure summarises key findings from the analysis of information asymmetry with CoE. For each link, the figure reports a weighted average score of association across studies (weighting: number of observations), with studies rejecting (confirming) the association being assigned zero (100) points and those finding mixed results given 50 points. Panel A (Panel B) shows average scores for different CoE (Microstructure) proxies.*